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Description	

Agent-Based Simulation for Kansei Engineering
-- Testing a new Fuzzy Linear Quantification Method in an Artificial World

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ABSTRACT

This paper argues that agent-based simulation can be used as a way for testing Kansei Engineering methods which deal with the human reaction from sensory to mental state, that is, sensitivity, sense, sensibility, feeling, esthetics, emotion affection and intuition. A new fuzzy linear quantification method is tested in an artificial world by agent-based modeling and simulations, and the performance of the fuzzy linear method is compared with that of a genetic algorithm. The simulations can expand people's imagination and enhance people's intuition that the new fuzzy linear quantification method is effective.

Keywords: Agent-based simulation, Kansei engineering

1. Introduction: Agent-Based Modeling for Testing Kansei Engineering Methods

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. Agents in the ABM can be simply defined as autonomous decision-making entities (see E. Bonabeau, 2002). 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 (see M. Wooldridge and N. Jennings 1995). ABM is thought as a powerful tool for studying complex adaptive systems which are systems with multiple elements/entities adapting or reacting to the pattern these elements create together (see W.B. Arthur, 1999). It is difficult to catch those features related to heterogeneous entities and their interaction and adaptive behaviors with conventional optimization approaches, equilibrium analysis, and other analytical techniques. ABM is not only a good tool for dealing with those features, but also provides a way for rethinking the dynamics of systems (see M. R. Resnick, 1994). Examples of the applications of agent-based modeling include: Bunn and Oliveira [5] used agent-based simulation to develop detailed insights into potential electricity market ahead of the introduction of new electricity trading arrangements of England and Wales; Stephan and Sullivan [13] put forward an agent-based model to study the transition of a personal transportation system based on conventional fuels to one based on alternative fuel, such as hydrogen; T. Ma and Y. Nakamori’s agent-based model for technological innovation (see, T. Ma and Y. Nakamori, 2005), and so on.

This paper argues that agent-based simulation can be used as a way for testing Kansei Engineering methods. Kansei, as a term in research, is originated from Japanese. It means the human reaction from sensory to mental state, that is, sensitivity, sense, sensibility, feeling, esthetics, emotion affection and intuition. From a business view, Kansei Engineering, Kansei Marketing, Kansei Design, or Kansei Evaluation are all one and the same thing, and the aim of research with these terms is “manufacturing products by appealing to Kansei of human beings” (see S. Nagasawa 2002).

For validating a method dealing with Kansei, usually it is necessary to test the result of the method in real world. For example, suppose a product is developed by Kansei Engineering, is it really the product that most of consumers will like? For answering this question, it is necessary to collecting consumers' evaluation, the sale data of the product or something like that. It is time and resource consuming for collecting the real data. So we argue that agent-based simulation can be used as a supplement method for getting the answer to the question. Of course the agent-based simulation can not substitute the real investigation because the result of agent-based simulation is based on some assumptions, not on measurement on the real world. Agent-based simulation can benefit the Kansei Engineering from the following two points:

- It provides a fast and cheap way for testing the performance of methods dealing with Kansei. Although it can not completely convince people whether the methods are effective or ineffective, it can aid people's intuition on the performance of the methods, especially in the process of developing a new method dealing with Kansei. The social investigation on the result of Kansei Engineering only can be carried out after product (at least samples) has been produced, while agent-based simulation enable researchers to test the methods dealing with Kansei before the method is used to produce products. This is very important for researchers to improve their methods, and it is also very important for firms to reduce costs and risk.

- It can generate enough scenarios and to show the performance of the methods dealing with Kansei under those different scenarios. Real social investigations are often limited by time, cost or other factors. So most of time, social investigations can only be carried out under some certain situations. For example, it is very difficult for a company located in Japan to do investigation in the county area in other countries. While in agent-based simulation, people can create enough scenarios by defining different rules for agents and setting different values to parameters.

The rest of this paper will present agent-based modeling and simulation for testing a new fuzzy linear quantification method developed by Yoshiteru Nakamori and Mina Ryoke (see Y. Nakamori, 2003; Y. Nakamori and M. Ryoke, 2001), as an example to show how agent-based simulations can aid Kansei Engineering. The fuzzy linear method deal with qualitative data obtained when a number of people evaluate the same objects with categorical attributes, and the main technique is a mapping of the data of individual evaluations into the model parameter space, preserving the relations between opinions of evaluators as much as possible.

Two kinds of actors are considered in the agent-based model, producers and consumers. Here the producers belong to the same industry, for example the automobile industry. At each time step, every producer produces several types of products, and every consumer evaluates several products in the market and purchases one which can bring him/her the maximal utility. Consumers are heterogeneous in the sense that they have different preference when evaluating products. And producers will improve their products based on sale records of different product types. For testing whether the fuzzy linear method is effective or not, we assume some producers will improve their products with a genetic algorithm, and some will improve their products with the fuzzy linear model, then we compare the performance – how much market share they obtain – of these producers.

Every product is composed of *N* design elements, and as a commodity, every product has *U* functions which can bring utilities to consumers. For consumers, design elements hide behind functions. For example, when purchasing a digital camera, consumers will consider *compatibility* which can be considered a function. Most consumers will not consider whether the camera uses a serial or parallel interface because they do not understand what a serial or parallel interface is. But for the technicians who design digital cameras, *interface* is a design element they must consider, and *serial* and *parallel* are two design values of this design element. The *interface*, with other design elements, will decide the *compatibility* of a digital camera. Also the *interface* will influence other functions, such as the *appearance* of a digital camera. From the above example, we can see that the relationship between design elements and functions is something like a genotype-phenotype map. A modified *NK* model was used to deal with the genotype-phenotype map between the design elements and the functions.

The methodology we have adopted accords with Axelrod's description of the value of simulation:

> *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* (see Axelrod 1997).

The rest of the paper is organized as follows. Section 2 briefly introduces the fuzzy linear method with an example. Section 3 presents the agent-based model and the simulations of comparing the fuzzy linear method and a genetic algorithm. Section 4 summarizes this paper.

2. The New Fuzzy Linear Quantification Method

The fuzzy linear method deal with qualitative data obtained when a number of people evaluate the same objects with categorical attributes, and the main technique is a mapping of the data of individual evaluations into the model parameter space, preserving the relations between opinions of evaluators as much as possible. It is a typical Kansei Engineering method.

The rest of this section will briefly introduce the fuzzy linear method and presents a simple example to explain its main function. The following are some basic notions of the method.

- **Objects for evaluation**. For instance, a lady is about to purchase a new dress from several dresses or a personnel manager is interviewing several candidates for employment, these dresses and candidates are objects for evaluation.

- **Measures of subjective evaluation**. For instance, *convenient* and *deluxe* may be used in a product rating, *comfortable* and *natural* are often used when mentioning residential environment, and *reliable* and *lovely* are used for one's character.

- **Evaluators**. For example, the lady and the personnel manager in the above examples are evaluators. They are also called subjects.

- **Attributes of objects**. Often, the attributes concerned here are categorical, for instance, color, type or pattern.

Suppose there are M objects for evaluation and K evaluators, and each objects has I attributes. Denote the value of an attribute i of the object m by $x_{mi}\left(m=1,2,\cdots,M,i=1,2,\cdots,I\right)$ and denote evaluator k's evaluation on object m by $y_{mk},(m=1,2,\cdots,M,k=1,2,\cdots,K)$. Then for the same input vector $\left(x_{m1},x_{m2},\cdots,x_{mI}\right)^t$, there are K outputs $\left\{y_{m1},y_{m2},\cdots,y_{mK}\right\}$. Based on the average data in evaluators:

$$y_m=\frac{1}{K}\sum_{k=1}^{K}y_{mk},m=1,2,\cdots,M \quad , \tag{1}$$

a regression model can be identified:

$$y_m=a_0+\sum_{i=1}^{I}a_i x_{mi}+e_m,m=1,2,\cdots,M \ . \tag{2}$$

Suppose

$$y=\left(y_1,y_2,\cdots,y_m\right)^t, \tag{3}$$

$$X=\begin{pmatrix}1 & x_{11} & x_{12} & \cdots & x_{1I}\\ 1 & x_{21} & x_{22} & \cdots & x_{2I}\\ \vdots & \vdots & \vdots & \ddots & \vdots\\ 1 & x_{M1} & x_{M2} & \cdots & x_{MI}\end{pmatrix}, \tag{4}$$

$$a=\left(a_0,a_1,\cdots,a_I\right)^t, \tag{5}$$

$$e=\left(e_1,e_2,\cdots,a_M\right)^t. \tag{6}$$

If X^tX is non-singular, by the method of least squares:

$$\|e\|^2\rightarrow \text{minimize} \tag{7}$$

The regression coefficients and residuals are given as

$$\hat{a}=\left(X^tX\right)^{-1}X^ty, \tag{8}$$

$$\hat{e}=y-X\hat{a}. \tag{9}$$

The values of output by each evaluator $y_k=\left(y_{1k},y_{2k},\cdots,y_{Mk}\right)^t$ can be mapped into the parameter space by the equation:

$$\hat{a}=\left(X^tX\right)^{-1}X^t\left(y_k-\hat{e}\right). \tag{10}$$

The following two equations are easily verified:

$$\frac{1}{K}\sum_{k=1}^{K}\hat{a}_k=\hat{a}, \tag{11}$$

$$\|y_k-y\|^2_{X\left(X^tX\right)^{-1}X^t}=\|\hat{a}_k-\hat{a}\|^2_{X^tX} \tag{12}$$

Eq. (11) means the average of regression parameters of all evaluators is equal to the parameter calculated by the average data. And Eq. (12) denotes how the variance-covariance structure between evaluators in the output data is preserved in the parameter space. And the mapping has the implication that $\hat{a}_k$ minimizes the square norm $\|y_k-X\hat{a}_k-\hat{e}\|^2$.

The new fuzzy linear method introduces a fuzzy vector *A* into the parameter space using the regression parameters. The membership function of *A* is defined as:

$$\mu_A(a) = \exp\left\{-\|a-\hat{a}\|^2_{D_A^{-1}}\right\}. \tag{13}$$

Then the output membership function of the fuzzy model:

$$Y = Ax \tag{14}$$

is given by

$$\mu_Y(y) = \max_{\{a|y=a^t x\}} \mu_A(a) = \exp\left\{-\left(y-\hat{a}^t x\right)^2 \left(x^t D_A x\right)^{-1}\right\}. \tag{15}$$

The positive-definite matrix D_A in Eq. (15) is defined as follows:

- Let the variance-covariance matrix of parameters $\hat{a}, \hat{a}_1, \cdots, \hat{a}_k$ in the (*I*+1)-dimensional space be S_A, and let

$$D_A = cS_A. \tag{16}$$

- Determine c in Eq. (16) so that the inequality in Eq. (17) is satisfied.

$$\mu_A(a_i) \geq h, i = 1, 2, \cdots, I. \tag{17}$$

Here the *h* is determined subjectively.

Here is an example to show the function of the fuzzy linear method. Suppose there are 10 objects, as shown in Table 1. Each object can be identified by two attributes which are *color* and *size*. The *color* attribute has 4 values which are "Black" (B), "Red" (R), "Green" (G) and "Yellow" (Y), while the *size* attribute has three values which are "Small" (S), "Middle" (M) and "Large" (L).

Suppose five customers evaluate the 10 objects with two measures which are *appearance* and *price*, as shown in Table 2 and Table 3, respectively.

After using the fuzzy linear quantification regression, the Green and Large object will be selected. Simply speaking, this method tries to give an optimizing or desirable object by applying a new fuzzy linear technique along with backward reasoning to deal with both objective data and subjective data. In the following section, the fuzzy linear regression method will be tested by agent-based simulations.

Table 1: 10 objects with two attributes

Objects	Color				Size		
	B	R	G	Y	S	M	L
O_1	●				●		
O_2		●			●		
O_3			●		●		
O_4				●	●		
O_5	●					●	
O_6		●				●	
O_7			●			●	
O_8				●			●
O_9	●						●
O_{10}		●					●

A ● indicates the attribute value that an object has.

Table 2: Evaluations with the *appearance*

	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	O_9	O_{10}
E_1	1	4	4	4	7	8	8	9	9	10
E_2	3	3	4	4	6	5	10	7	7	9
E_3	2	3	3	6	6	9	6	9	10	7
E_4	3	2	3	7	5	7	7	10	8	10
E_5	2	5	5	3	7	9	10	7	10	8

Table 3: Evaluations with the *price*

	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	O_9	O_{10}
E_1	1	5	3	6	4	6	7	8	9	8
E_2	4	3	4	6	2	7	9	7	10	7
E_3	3	4	5	4	5	5	8	5	10	6
E_4	3	5	2	4	6	6	7	5	8	5
E_5	2	5	3	5	5	4	7	4	8	6

3. Testing the New Fuzzy Linear Method by Agent-Based Simulations

3.1 The agent-based model

There are two kinds of actors (or agents) included in the agent-based model. One kind is producers, the other is customers. Every producer will produce several types of products at every time step. With several functions, each product is composed of several design elements. Every customer has different weight for different function. The weighted average method has been widely used in evaluating. It is pertinent to model the customers' evaluating behavior by assigning different weights for different functions to customers.

For those notions in the fuzzy linear method, their equivalents in our agent-based model are:

- The equivalents of **objects for evaluation** in the agent-based model are **products**. Products will be evaluated by consumers.
- The equivalents of **Measures of subjective evaluation** are the phenotype **functions** of products. Consumer agents will measure whether a product fits him/her by the functions of the product.
- The equivalents of **Evaluators** are **consumers**. Consumers will evaluate several products when purchasing.
- The equivalents of **Attributes of objects** are **design elements of products**.

The following mathematical symbols are independent from those introduced in Section 2.

Suppose there are S producers, the set of producers can be denoted as:

$$\mathbf{P} = \{P_1, \cdots, P_S\} . \tag{18}$$

At every time step, each producer will produce L_i types of products, for producer P_i (i = 1, …, S), its product types at time step t are:

$$\mathbf{A}_{Pi}^{t} = \{A_{i1}^{t}, \cdots, A_{iLi}^{t}\},\ i = 1, \cdots, S\ . \tag{19}$$

Any product is composed of N design elements. There is a general design space **G**, denoted in Eq. (20), which includes the N design elements. The T in Eq. (20) denotes the transpose of the matrix.

$$\mathbf{G} = (\mathbf{g}_1, \cdots, \mathbf{g}_N)^T\ . \tag{20}$$

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

$$\mathbf{g}_i = (g_{i1}, \cdots, g_{iHi}),\ i = 1, \cdots, H_i\ . \tag{21}$$

For every producer, the values of its design elements are generated from the **G**, so

$$\mathbf{G}_{Pi} \subseteq \mathbf{G},\ i = 1, \cdots, S\ . \tag{22}$$

For example, if N = 4 and H_i = 3 (i = 1,2,3,4), the **G** and the design space of a certain producer P_{i*} are:

$$\mathbf{G} = \begin{pmatrix} g_{11} & g_{12} & g_{13} \\ g_{21} & g_{22} & g_{23} \\ g_{31} & g_{32} & g_{33} \\ g_{41} & g_{42} & g_{43} \end{pmatrix} \text{ and } \mathbf{G}_{Pi*} = \begin{pmatrix} g_{11} & 0 & g_{13} \\ g_{21} & 0 & 0 \\ g_{31} & 0 & g_{33} \\ 0 & g_{42} & g_{43} \end{pmatrix}.$$

In $\mathbf{G}_{pi*}$ the 0 means producer P_{i*} has no such design value corresponding to the position in **G**.

Every product has U functions (fitness components):

$$\mathbf{F} = \{f_1, \cdots, f_U\}\ . \tag{23}$$

The fitness value of every function ranges from 0 to 1, i.e.

$$f_i \in [0,1], i = 1, \cdots, U\ . \tag{24}$$

NK model (see S. Kauffman 1993) is used to illustrate map between design elements and functions 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. Looking the design elements as genes, the generalized version of the *NK* model (see L. Altenberg 1994) can be described as the following:

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

$$\mathbf{M} = (m_{ij})_{N \times U},\ i = 1, \cdots, N;\ j = 1, \cdots, U\ , \tag{25}$$

of indices $m_{ij} \in \{0,1\}$, where $m_{ij} = 1$ indicates that gene i affects fitness component j. **M** is randomly
initialized in the simulation.

The columns of **M**, called the polygeny vectors, $q_j = (m_{ij})_{N \times 1} (i = 1, \ldots, N)$, give the genes controlling each fitness component j. The rows of **M**, called the pleiotropy vectors, $q_i = (m_{ij})_{1 \times U} (j = 1, \ldots, U)$, give the fitness components controlled by each gene i.

If any of the genes controlling a given fitness component mutates, the new value of the fitness component will be uncorrelated with the old. Each fitness component is a uniform pseudo-random function of the genotype, $x \in \{0,1\}^N$

$$f_i(x) = f(x \circ q_i; i, q_i) \sim \text{uniform on } [0,1] , \tag{26}$$

where

$$f : \{0,1\}^N \times \{1, \cdots, N\} \times \{0,1\}^N \to [0,1] . \tag{27}$$

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 fitness component is affected by no genes, it is assumed to be zero:

$$f_i(x) = f(x \circ q_i; i, q_i) = 0 \text{ , if } q_i = (0 \cdots 0) . \tag{28}$$

In the traditional *NK* model, the total fitness is defined as the normalized sum of the fitness components:

$$FC = \frac{1}{U} \sum_{i=1}^{U} f_i . \tag{29}$$

We make the following two changes 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 only two values 0 and 1. This is acceptable because it is not necessary that every design element has only two design values. For example, considering *engine* is a design element, when designing a new car, technicians can select one from dozens of different engines.

- In the traditional *NK* model, if any of the genes controlling a given fitness component mutates, the new value of the fitness component will be uncorrelated with the old. Each fitness component is a uniform pseudo-random function of the genotype. Sometimes things in real world are a little different from the above situation. For example, suppose the product is a racing car, one of the two design elements is engine type, the other design element is the height of the car, and the function is the maximal speed of the racing car. According to the traditional *NK* model, it is possible to get a landscape like Fig. 1. But it does not accord with our common sense that the lower a racing car is, the higher its maximum speed is. So we changed “if any of the genes controlling a given fitness component mutates, the new value of the fitness component will be uncorrelated with the old” to “a function’s value is the average of all the contribution of those genes contributing to it, and when a gene change, its contribution will change, but other genes’ contribution remain the same”. Then we can get a reasonable landscape like in Fig. 2.

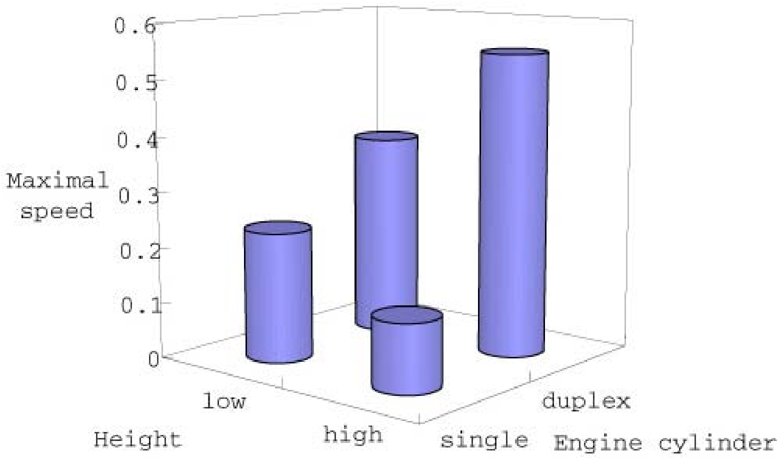

Figure 1: An unreasonable landscape

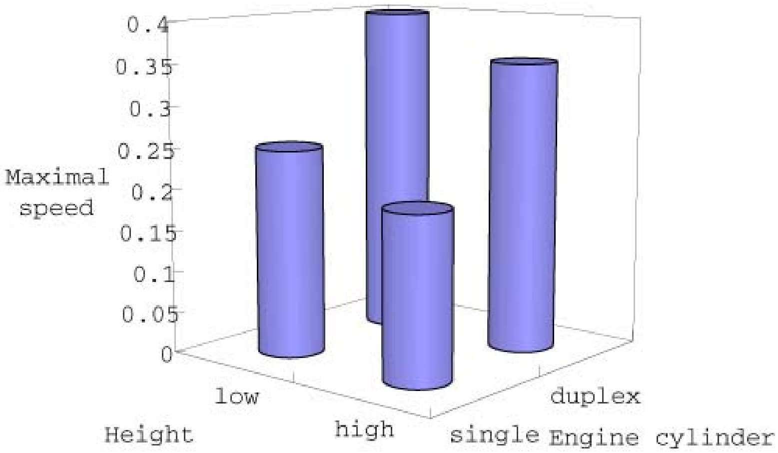

Figure 2: A reasonable landscape

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. In the simulation, we use the following weighted average evaluating method.

Suppose the number of consumer is R, the set of consumers can be denoted as:

$$\mathbf{C} = \{C_1, \cdots, C_R\}. \tag{30}$$

For any consumer C_j (j = 1, …, R), its weights for different functions can be denoted as:

$$\mathbf{W}_{Cj} = \{w_{1Cj}, \cdots, w_{UCj}\},\ j = 1, \cdots, R\ , \tag{31}$$

subject to

$$\begin{cases} w_{iCj} \in [0,1],\ i = 1, 2, \cdots U \\ \sum_{i=1}^{U} w_{iCj} = 1 \end{cases}. \tag{32}$$

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

$$E = \sum_{i=1}^{U} w_i f_i \ . \tag{33}$$

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

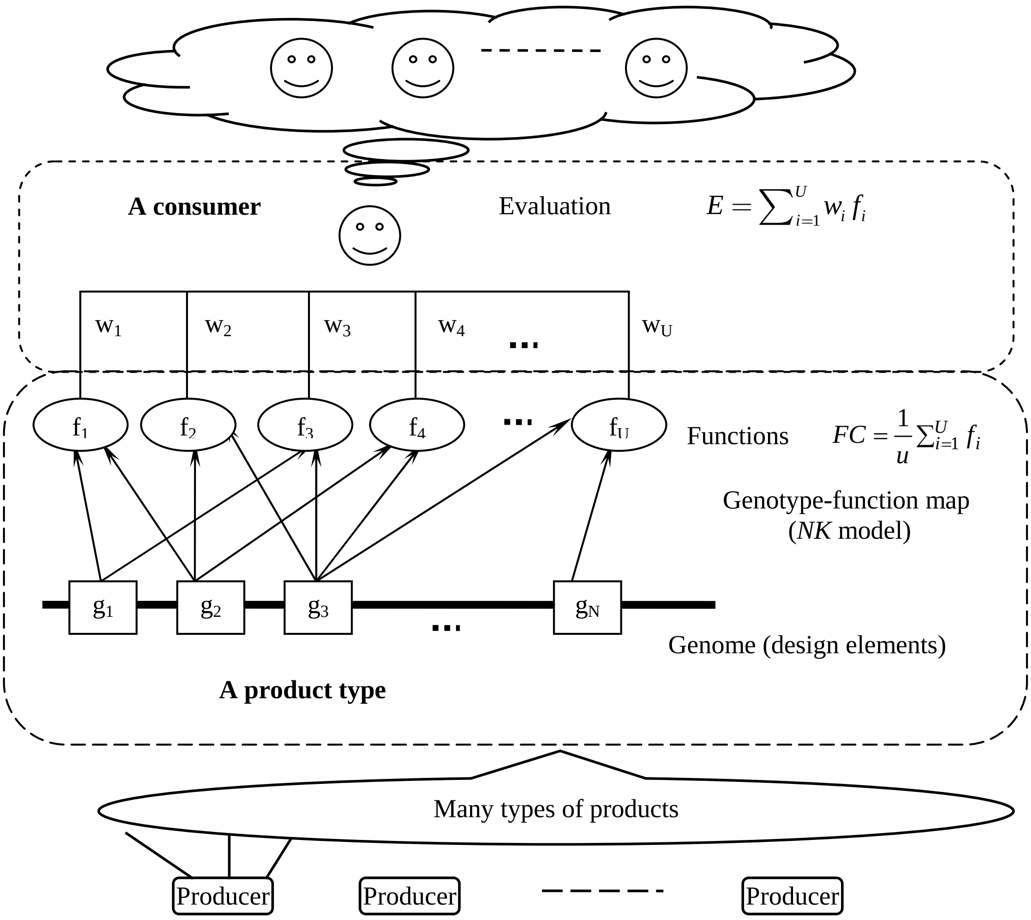

Figure 3 The framework of the agent based model

As shown in Fig. 3 which describes the framework of the agent-based model, there are several producer agents, and each of them will produce several types of products. With several functions (or performance parameters), each product is composed of several design elements. The modified ***NK*** model is used to deal with the mapping from design parameter space (DPS) to performance parameter space (PPS). There are a lot of heterogeneous consumers in the market who will evaluate the product types in the market. At each step, each consumer will select the product type he/she evaluates highest. Producers will improve their products according to some certain methods. In the following subsection, we will compare two methods of improving products, one is the fuzzy linear method introduced in Section 2, and the other one is a genetic algorithm.

3.2 Testing the fuzzy linear method

In this section, the fuzzy linear regression method will be tested by using the agent-based model. The following is the initialization for the simulations:

- $N = 3$, $U = 5$, and $H_i = 4$ ($i = 1, \ldots, 3$), which mean every product is composed of 3 design elements and has 5 functions, and every design element has 4 design values. So totally there can be $3^4 = 81$ types in the industry.

- $S = 3$, $L_i = 50$ ($i = 1, \ldots, 3$), which mean there are three producers, and at each time step, every producer will produce 50 product types.

- $R = 1000$, which means there are totally 1000 consumers.

- There are 50 kinds of customers. That means consumers can be divided into 50 groups according to their preferences.

- Customers are partly informed about the market. Before a consumer-agent makes the decision to purchase a product, it will evaluate 20 types which are randomly selected from the market, not all the types (81 types) in the market.

- At time step 10, producer 1 using the fuzzy linear quantification model to design next generation product type.

Fig. 4 shows the sale volumes of the three producers. We can see after using the fuzzy linear regression method, producer 1 gets much market share from the producer 2. Before time step 10, producer 2 is the leader (it has the biggest market share) in the market, and producer 1 and producer 3 almost can sale nothing[1]. After time step 10 when producer 1 using the fuzzy linear method, producer 1 becomes the market leader, that means the fuzzy linear regression method help producer 1 make a progress in improving its products.

In the above simulation, producer 2 and producer 3 do not improve their products. In the following simulation, besides the above initializations, we set that the producer 2 and producer 3 improve their products by using the following GA (genetic algorithm).

Suppose the set of all product types in market at a certain time step is:

$$\mathbf{A} = \{A_1, \cdots, A_B\} . \tag{34}$$

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

$$\mathbf{S} = \{s_1, \cdots, s_B\} . \tag{35}$$

For each product type, the bigger the amount in which it is sold in the last term, the more the opportunity it has to be selected as a genome of the next generation types. Suppose s_{min} is the minimum value in set $\mathbf{S}$, then for every product type A_u ($u = 1, \ldots, B$) in set $\mathbf{A}$, its probability of being the genome type of the next generation products is:

$$P(A_u) = (s_u - s_{\min}) / \sum_{j=1}^{B} (s_j - s_{\min}) . \tag{36}$$

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[1] This is a result caused by the random initialization of the general design space and each producer's design space.

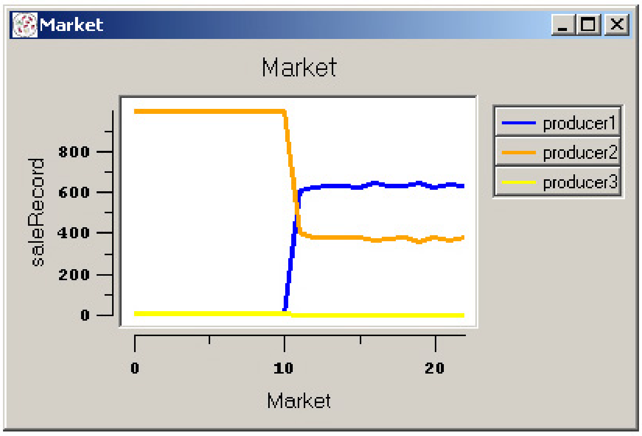

Figure 4: Sale volumes of the three producers
– producer 2 and producer 3 do not improve their products

The new products are generated from genome types by crossover and mutation. For two selected genome types, crossover is an operator that cuts their chromosome strings at some randomly-chosen position. Thus two "head" segments and two "tail" segments are produced. 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 our simulation, the crossover rate is set to be 0.7, and the mutation rate is set to be 0.02.

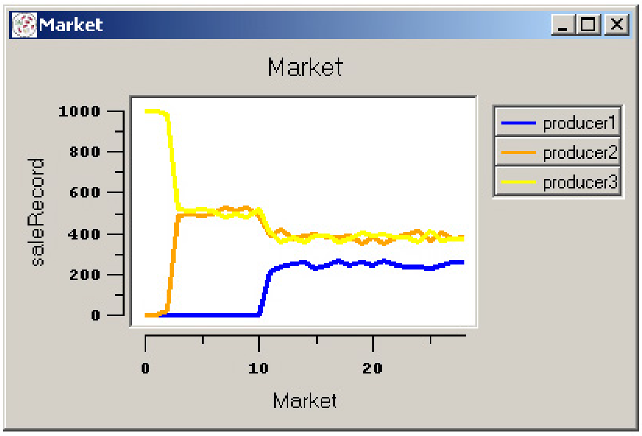

Figure 5: Sale volumes of the three producers
– producer 2 and producer 3 improve their products by GA

The Fig. 5 shows that before time step 10, producer 2 and producer 3 occupy all the market by using the genetic algorithm to improve their products. But after time step 10, producer 1 obtains some market share by using the fuzzy linear regression method.

The difference between the genetic algorithm and the fuzzy linear method is: the genetic algorithm improve the products little by little, it is a long-term process, and it is difficult to say how long time it will take for improving products to a desirable level, considering the species in nature improve themselves by billions of years and they are still in the process of improving; while the fuzzy linear method is a non-time consuming process (if the time for collecting data and processing can be ignored, which is also needed in the GA), i.e., the product improving happens at a time point, which is time step 10 in our simulation. The increasing competition in the market needs firms to have quick response and improvement. Looking the process of incremental product improving as an evolutionary process, product improving and innovation can be described and simulated by using genetic algorithm, but genetic algorithm is not a effective and feasible way for firms' improving their product in practice. In real world, the fuzzy linear regression method is more effective and feasible for firms' improving products, rather than the genetic algorithm.

Here we summarize the two experiments. In the first experiment, we assumed producer agent 1 improved its products by using the fuzzy linear method, while producer agent 2 and 3 did not improve its products. With this experiment, we were not comparing the fuzzy method with any other method. What we aimed to see was whether the fuzzy method can improve the products or not. And the experiments showed it could, as the market share of producer agent 1 increased a lot after applying the fuzzy method. In the second experiment, we assumed producer agent 1 still improved its products by using the fuzzy linear method, and producer agent 2 and 3 improved their products by using a genetic algorithm. With this experiment, we did not aim to compare the performance of the genetic algorithm and that of the fuzzy method. What we aimed to see was weather the fuzzy method could work when other agents continuously improve their products. And the experiment showed it could since the market was totally occupied by producer agent 2 and 3 before agent 1 applied the fuzzy linear method, and after applying the fuzzy method, agent 1 got some market share.

4. Concluding Remarks

This paper argued that agent-based simulation can be used as to aid Kansei Engineering. A new fuzzy linear quantification method is tested in an artificial world by agent-based modeling and simulation, and the simulations can expand people's imagination and enhance people's intuition that the new fuzzy linear quantification method is effective.

Agent-based simulation enable researcher to test methods of Kansei Engineering in different scenarios. For the simulation introduced in this paper, people can assume different evaluating methods of consumers and setting different values to the parameters according to informed knowledge to see the performance of the linear fuzzy method in different scenarios.

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