Expert Systems with Applications 38 (2011) 7270–7276

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Agent-based diffusion model for an automobile market with fuzzy TOPSIS-based product adoption process

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ARTICLE INFO

Keywords:
Product diffusion
Automobile market
Agent-based model
Fuzzy TOPSIS
Social influence

ABSTRACT

This paper focuses on the product diffusion in a competitive automobile market. Since purchasing a car is costly, the consumers in the market tend to behave like rational decision makers. They naturally compare the attributes of cars (e.g., brand preference, fuel economy, safety, comfort) and make overall decisions. In this paper, we propose an agent-based (AB) diffusion model consisting of tens of thousands of interacting agents. In the model, an agent represents a consumer and bases its multi-attribute decision-making on fuzzy TOPSIS. The decision-making process integrates three purchasing forces: expert's product information provided by mass media, subjective weights on product attributes assigned by individual consumers, and social influence (i.e., information delivered from a consumer's neighbors who have already adopted products). The AB model executes the agents and observes the collective behavior. In this sense, the model can assist in the analysis of the complex market dynamics. We conducted an empirical study to verify the performance of the AB model.

1. Introduction

Automobile markets are highly competitive. In the markets, similar functioning cars compete with each other for expanding their market shares, so launching new cars into the markets introduce a considerable amount of risk to the carmakers. To reduce the risk, the carmakers need to analyze how critical marketing and production decisions (e.g., promotion strategy, price, supply volume) give impact on the market shares of the new cars, based on which the firms can choose the best decisions that achieve maximum profits from the new cars. However, such "what-if" analysis is a quite difficult task and requires elaborate forecasting tools. It is traditional to use time-series techniques (Box, Jenkins, & Reinsel, 1994; Cheng, Chen, & Wu, 2009) for the analysis, but the techniques require accumulated sales data as inputs, thus they are of no use when a brand-new car is released into a market. In such situation, it is possible that marketers analyze the individual product adoption processes of heterogeneous consumers and investigate how market dynamics emerge from the individual adoptions.

In this paper, we develop an agent-based (AB) model for forecasting product diffusion in a full-sized car market. The central issue of this paper is how exactly the AB model can predict the market dynamics when a new car is released into the market. The AB model consists of tens of thousands of interacting autonomous agents. In the model, an autonomous agent represents a consumer and has unique characteristics as a consumer to make its own purchase decision. A set of consumer-agents with their interaction structure corresponds to a social network of consumers and can be counted as a virtual market. In the real world, the product information evaluated by early product adopters spread out through communication channels such as the Internet and word-of-mouth. The information influences on the purchase decision of potential consumers, which is called social influence or word-of-mouth effect (Bone, 1995). In the AB model, social influence is raised by the interaction among the consumer-agents. The AB model executes the consumer-agents, which can be of different types, and observes the collective behavior. In this sense, the model can assist in the analysis of the complex market dynamics.

The proposed AB model reflects two realistic human behavioral factors relating to product adoption process: heterogeneity of consumers and fuzzy decision-making based on multiple attributes. Consumers are heterogeneous. First, consumers have different weights on the importance of product attributes and they usually express the weights in linguistic terms. For instance, a consumer may rate "very important" for the fuel economy of car, whereas another may perceive that the attribute is "not important." Second, consumers are unlikely to buy a new product when social influence is negative. On the other hand, the chance of buying the new product becomes higher as social influence increases positively. However, in general, to what extent consumers accept social influence is different according to individual characters. Some people with strong personality might not be susceptible to social influence, while others who are very sensitive to the trend of public

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doi:10.1016/j.eswa.2010.12.024

opinion accommodate themselves to the decisions of early product adopters.

When several high-priced products with similar functions are competed in a market, it is not easy to decide one product is superior to the others in all aspects without difficulty. In such condition, consumers tend to be more than prudent; they will behave like rational decision makers. Because the performance of products are usually evaluated with respect to individual attributes (e.g., brand preference, fuel economy, safety, comfort), consumers naturally compare the products in an attribute-by-attribute fashion, based on which they make overall purchase decisions. Consumers can access the product evaluation information through mass media, such as *Consumer Reports* and the Internet, and through the word-of-mouth spread over in the social network of consumers. However, in many cases, the product information is not expressed quantitatively. People are used to compare product attributes relatively with linguistic terms such as good, normal, or bad. For example, consumers compare the safety of competing cars and may say "the safety of this car is good but for that car it is bad." The relative evaluation with linguistic terms is common in our life.

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a multi-attribute decision-making heuristic. It selects the best solution from many alternatives, which is the closest to the positive ideal solution and the farthest from the negative ideal solution. Its logic is similar to a rational human decision-making process (Hwang & Yoon, 1981). We adapt TOPSIS using fuzzy set theory for transforming a linguistic evaluation into a crisp number. Modeling using fuzzy set theory has proven to be an effective way for formulating decision problems where information available is subjective and imprecise (Zimmermann, 2001).

Fuzzy TOPSIS has been introduced for various multi-attribute decision-making problems (Chamodrakas, Alexopoulou, & Martakos, 2009; Chu, 2002; Dağdeviren, Yavuz, & Kilinç, 2009; Sun & Lin, 2009; Wang & Chang, 2007). In this paper, we adapt fuzzy TOPSIS for modeling consumer's product adoption process, which integrates three purchasing forces: (1) expert's product information provided by mass media, (2) subjective weights on product attributes given by individual consumers, and (3) social influence (i.e., information delivered from a consumer's neighbors who have already adopted products). The expert's product information is assumed to be objective and accessible by all consumers. Each consumer personalizes the product information by reflecting his/her own weights on product attributes and makes purchase decision based on the personalized product information and social influence.

Traditionally, analytical approaches formalize the aggregate level of penetration of a new product based on differential equations. The Bass model and its variants illustrate the diffusion process of product or technology quantitatively at a macro-level (Mahajan, Muller, & Bass, 1990; Meade & Islam, 2006; Wang & Chang, 2009). The models are able to include social influence by classifying consumers into categories such as early adopters and imitators – the latter follows the product choice pattern of the former. However, the people in each group are assumed to be homogeneous; the models are unable to specify at a micro-level how individual consumers respond to a new product and how consumers communicate and influence each other in competitive markets (Chandrasekaran & Tellis, 2007; Rahmandad & Sterman, 2008). On the other hand, AB models are computational tools at micro-level. The models are able to imitate a natural market dynamics by specifying individual product adoption processes and implementing word-of-mouth which is again fed back to individual decision-making of potential consumers. Some recent studies based on AB models are capable of representing individual product adoption processes (Alkemade & Castaldi, 2005; Delre, Jager, Bijmolt, & Janssen, 2007; Delre, Jager, & Janssen, 2007; Song & Chintagunta, 2003; Zenobia, Weber, & Daim, 2009). However, the previous AB models do not consider consumer's product adoption process from the viewpoint of a multi-attribute decision-making problem, or not reflect linguistic product evaluation and consumer's weights to the product adoption process.

The rest of the paper is organized as follows. In Section 2, we present the proposed AB model. In Section 3, we conduct an empirical study to validate the model's feasibility. Finally, in Section 4, we conclude the implications from the results and mention on the future research directions.

2. Agent-based model

2.1. Individual decision-making

Suppose that an automobile market consists of m products of P_i ($i = 1, \dots, m$) and the products are evaluated based on a set of n attributes A_j ($j = 1, \dots, n$). The expert's performance ratings on the products are represented as a matrix of $E = (r_{ij})_{m\times n}$

$$E = \begin{array}{c} \\ P_1 \\ P_2 \\ \vdots \\ P_m \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & \cdots & A_n \end{array} \\ \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \dots & \vdots & \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \end{array} \tag{1}$$

In the matrix, the rating r_{ij} of product P_i with respect to attribute A_j is represented using the linguistic terms given in Table 1 in which each linguistic term is characterized by a triangular fuzzy number. As the first step of product adoption process, consumers are assumed to access the expert's product information E through mass media.

Let $W_k = (w_{1k}, \dots, w_{nk})$ be a weight vector for n attributes A_j ($j = 1, \dots, n$) assigned by consumer-agent k using the linguistic terms in Table 1. The weight vector represents the relative importance of the attributes perceived by the consumer-agent. The performance rating matrix $S^k = (x^k_{ij})_{m\times n}$ personalized by the consumer-agent can be derived by multiplying the weight vector W_k and the expert's product information matrix E. The personalized product information matrix S^k reflects the evaluation bias of the consumer-agent k on the m products. However, since the matrix E and the weight vector W_k are composed of linguistic ratings represented as triangular fuzzy numbers, a fuzzy operation is required in order to multiply the triangular fuzzy numbers r_{ij} and w_{jk}. We apply the graded mean integration representation method (Chou, 2003) which provides easier understanding and simpler calculation for a multiplication of fuzzy numbers. The method converts a fuzzy number into a crisp value as follows (refer to Chou (2003) for the detailed logic).

Definition. The graded mean integration representation method transforms a triangular fuzzy number $X = (x_1, x_2, x_3)$ into a crisp number $P(\widetilde{X})$ by

$$P(\widetilde{X}) = \frac{1}{6}(x_1 + 4x_2 + x_3) \tag{2}$$

Property. The multiplication operator $\otimes$ of triangular fuzzy numbers $\widetilde{X}$ and $\widetilde{Y}$ is defined as

$$\begin{aligned} P(\widetilde{X} \otimes \widetilde{Y}) &= P(\tilde{X}) \times P(\tilde{Y}) \\ &= \frac{1}{6}(x_1 + 4x_2 + x_3) \times \frac{1}{6}(y_1 + 4y_2 + y_3) \end{aligned} \tag{3}$$

Using Eq. (3), the personalized product information matrix S^k is expressed as

Table 1
Linguistic terms and triangular fuzzy numbers.

Variable	Linguistic term				
Performance (r_{ij})	Poor (P)	Fair (F)	Good (G)	Very Good (VG)	Excellent (E)
Weight (w_{jk})	Very low	Low	Medium	High	Very high
Sensitivity to social influence (α_k)	Very weak	Weak	Normal	Strong	Very strong
Triangular fuzzy number $(r^1_{ij}, r^2_{ij}, r^3_{ij})$, $(w^1_{jk}, w^2_{jk}, w^3_{jk})$, $(\alpha^1_k, \alpha^2_k, \alpha^3_k)$	(0, 0, 0.3)	(0.1, 0.3, 0.5)	(0.3, 0.5, 0.7)	(0.5, 0.7, 1.0)	(0.7, 1.0, 1.0)

$$S^k = \begin{array}{c c} & \begin{array}{cccc} A_1 & A_2 & \dots & A_n \end{array} \\ \begin{array}{c} P_1 \\ P_2 \\ \vdots \\ P_m \end{array} & \begin{bmatrix} x^k_{11} & x^k_{12} & \dots & x^k_{1n} \\ x^k_{21} & x^k_{22} & \dots & x^k_{2n} \\ \vdots & \vdots & \dots & \vdots \\ x^k_{m1} & x^k_{m2} & \dots & x^k_{mn} \end{bmatrix} \end{array} \tag{4}$$

where $x^k_{ij} = P(r_{ij} \otimes w_{jk}) = \frac{1}{6}(r^1_{ij} + 4r^2_{ij} + r^3_{ij}) \times \frac{1}{6}(w^1_{jk} + 4w^2_{jk} + w^3_{jk})$. The matrix S^k is normalized to $\bar{S}^k = (\bar{x}^k_{ij})_{m\times n}$ by

$$\bar{x}^k_{ij} = \frac{x^k_{ij}}{\sqrt{\sum_{i=1}^m (x^k_{ij})^2}} \tag{5}$$

For the consumer agent k, the $\bar{x}^k_{ij}$ in Eq. (5) can be interpreted as the partial worth of product P_i for attribute A_j and the sum of $\bar{x}^k_{ij}$ for all attributes summarizes the attractiveness of product P_i. In traditional product choice models (see Manrai (1995) for the studies on product choice models), the attractiveness of the product is called utility. A consumer chooses a product using a random function of the utility. This research further considers social influence (i.e., word-of-mouth effect) in the selection of a product. As we previously mentioned, it is common that consumers respond to social influence with different degrees. In this paper, individual sensitivity levels to social influence are estimated through a survey and expressed with the linguistic terms defined in Table 1. The sensitivity level of the consumer-agent k, α_k, can be converted into a crisp value by using the graded mean integration representation method defined in Eq. (2). Suppose that the number of product adopters among the neighbors of the consumer-agent k is L_k and the trust levels of the neighbors are equal. Then overall performance rating of product P_i with respect to attribute A_j estimated by the consumer-agent k is given by

$$\begin{aligned} \bar{x}^k_{ij} &= (1-\alpha_k)\bar{x}^k_{ij} + \alpha_k \sum_{l\in L_k} \bar{x}^l_{ij}/|L_k| \\ &= \left\{1 - \frac{1}{6}(\alpha^1_k + 4\alpha^2_k + \alpha^3_k)\right\}\bar{x}^k_{ij} + \left\{\frac{1}{6}(\alpha^1_k + 4\alpha^2_k + \alpha^3_k)\right\} \sum_{l\in L_k} \bar{x}^l_{ij}/|L_k| \end{aligned} \tag{6}$$

With the matrix $\bar{S}^k$ updated using Eq. (6), the consumer-agent k determines the positive-ideal product P^{k+} and the negative-ideal product P^{k-} as

$$\begin{aligned} P^{k+} &= \{\bar{x}^{k+}_1, \bar{x}^{k+}_2, \dots, \bar{x}^{k+}_n\} \\ &= \{(\max_i \bar{x}^k_{ij} | j \in B), (\min_i \bar{x}^k_{ij} | j \in C) | i = 1, 2, \dots, m\} \\ P^{k-} &= \{\bar{x}^{k-}_1, \bar{x}^{k-}_2, \dots, \bar{x}^{k-}_n\} \\ &= \{(\min_i \bar{x}^k_{ij} | j \in B), (\max_i \bar{x}^k_{ij} | j \in C) | i = 1, 2, \dots m\} \end{aligned} \tag{7}$$

where B is a set of benefit attributes and C is a set of cost attributes. By definition, the positive-ideal product P^{k+} is optimal with respect to all attributes, and in reality, the product is almost unattainable. Most consumers will consider the positive-ideal product as a reference and choose the best alternative that is most similar to the positive-ideal product and most dissimilar to the negative-ideal product. Using the n-dimensional Euclidian distance, the similarities of product P_i to the two ideal products P^{k+} and P^{k-} can be measured by

$$d^{k+}_i = \sqrt{\sum_{j=1}^n (\bar{x}^k_{ij} - \bar{x}^{k+}_j)^2} \quad \text{and} \quad d^{k-}_i = \sqrt{\sum_{j=1}^n (\bar{x}^k_{ij} - \bar{x}^{k-}_j)^2} \tag{8}$$

By combining the two similarities, the relative closeness of product P_i to the positive-ideal products can be measured by

$$C^k_i = \frac{d^{k-}_i}{d^{k+}_i + d^{k-}_i}, \quad i = 1, 2, \dots, m \tag{9}$$

Finally, the consumer-agent k chooses the best product with the maximum closeness.

In this section, we discussed how individual consumer-agents rank competing products by taking multiple product attributes into consideration. In the following section, we will explain how we coordinate the execution of the consumer-agents for generating the diffusion dynamics.

2.2. Diffusion dynamics

Before presenting the execution procedure of the AB model, we discuss on three initial conditions for the execution. Those are the social network structure of consumers, the assignments of weight vectors and the sensitivity levels to social influence, and consumers' product purchase times.

First, a virtual market should be established to simulate a word-of-mouth process. The market is a social network consisting of consumer-agents (nodes) that are connected by acquaintanceships (links). In the social network, each consumer-agent makes a purchase through fuzzy TOPSIS and delivers its own personalized product information to its neighbors linked directly. The logical structure of the social network influences on the speed of word-of-mouth. The speed is fast if everyone in the network is reachable in a few steps. Otherwise, it takes many steps to deliver any information from one to another throughout the network. Watts and Strogatz (1998) classified social networks into three categories: regular network, small-world network, and random network. The regular network is a normal lattice where every node is linked to its neighbors with a fixed degree of connectivity. The small-world network emerges as the result of randomly rewiring a fraction of the links of every node. The fraction of links is called rewiring constant. In the small-world network, it is possible to connect any two nodes through just a few links. The random network is an extreme case where every link in the regular network is replaced with a random link. Empirical evidence suggests that social networks often display the property of small-world network (Watts & Strogatz, 1998). In this paper, we employ the small-world network as the logical model of the virtual market.

Second, each consumer-agent should have its own weight vector (W_k) and sensitivity level to social influence (α_k). In the AB model, these two characteristics are regarded as random variables and assigned to the consumer-agents in a probabilistic way. In detail, throughout a survey, respondents give their own weights for product attributes and sensitivity levels to social influence using linguistic terms. The acquired data are used for building the empirical distributions of the two random variables. Then each consumer-agent is assigned a random weight vector and a random sensitivity level by using the two empirical distributions, respectively.

Third, product diffusion starts from innovators who have a strong tendency to test a new product before others do. Their decisions are the seed for a wave of word-of-mouth. For each car entry time, the number of innovators is set to 2% of the non-adopters who do not purchase products until the entry time. We exclude the case that previous adopters repurchase cars in a short term. The number of innovators is given based on the assumption of the Bass model that innovators normally account for 0.2–2.8% of the population of a market (refer to p. 4 in Mahajan, Muller, and Wind (2000)). We assume that the number of innovators is not dependent on the number of car entries. If more than two cars are released at the same time, the number of innovators is just 2% of non-adopters remaining at the release time. Each of the innovators adopts a car among those that are released at the same time according to the fuzzy TOPSIS-based product adoption process.

Once innovators adopt, other consumer-agents (i.e., non-adopters) connected to them through a social network become aware of the product adoptions and the consumer-agents are participated in the word-of-mouth process. Within the diffusion horizon, the purchase times of the non-adopters are randomly determined using a uniform distribution. This assumption is reasonable for the markets of highly expensive consumer durables such as automobiles and high-end TVs, because people are used to buy new products when they just need (e.g., when their used ones become old), almost independently of when others do. However, this does not mean that the consumers in the markets are not sensitive to social influence. The consumers are exposed to social influence at their purchase times.

The execution procedure of the AB model consists of two phases. The initial phase configures the network of consumer-agents; makes them heterogeneous by assigning different weight vectors and sensitivity levels to social influence; sets the consumer-agents' purchase times. The execution phase starts the diffusion from the innovators at diffusion time zero. As the diffusion time passes, the consumer-agents whose purchase times are equal to the current diffusion time make purchase decisions with the consideration of information received from their neighbors connected to them through a social network. The diffusion continues until the current time reaches the end of the diffusion horizon. The execution procedure can be summarized as follows.

2.2.1. Assumptions

- $(m-1)$ products P_i $(i = 1, \dots, m-1)$ exist at diffusion time zero and a new product P_m is introduced at diffusion time t_{new}.
- Expert's product information for all products is available.
- For each time when a new product enters the market or new products enter at the same time, the number of innovators is set to 2% of non-adopters.

2.2.2. Initialization

(Step 1) Create a social network consisting of consumer-agents and their links.
(Step 2) Using a survey result, assign each consumer-agent a weight vector and a sensitivity level to social influence.
(Step 3) Except for the innovators, generate consumer-agents' purchase times according to a uniform distribution, *Uniform*(1, End-of-Horizon).

2.2.3. Execution

(Step 4) At diffusion time $t = 0$, introduce the expert's information on the $(m-1)$ products to all consumer-agents.
(Step 5) For the $(m-1)$ products, determine the locations of the innovators in the social network randomly and make each of them choose a product among the $(m-1)$ products according to the fuzzy TOPSIS-based product adoption process. Then, set $t = 1$.
(Step 6) If $t \neq t_{new}$, go to step 7. Otherwise, introduce the expert's information on the new product P_m to the current non-adopters. For the product P_m, determine the locations of the innovators in the social network randomly and make them choose the product.
(Step 7) For the consumer-agents whose purchase times are equal to the current time t, they request personalized product information to the neighbors who purchased any products before the current diffusion time t. Then they select their products according to the fuzzy TOPSIS-based product adoption process.
(Step 8) Set $t = t + 1$. If the diffusion time reaches the End-of-Horizon, then stop the diffusion. Otherwise, go back to step 6.

3. Empirical study

3.1. Description

Using an empirical study, we tested the performance of the agent-based diffusion. The empirical study is concerned with a full-sized car market in Korea. As of today, six car models exist in the market. Among those, we focused on three models, denoted as C1, C2, C3, because the remaining models have occupied very small market portions, which have little varied over time. The first two car models (C1 and C2) were entered into the market 38 months ago and the last model (C3) was released into the market next 19 months after the launch of C1 and C2. The main question addressed in the study was "can we forecast the dynamics of the car market with the AB model and, if so, how social influence contributes to the market dynamics?" Before answering the question, we needed to calibrate two parameters related to the social network of consumers. As we discussed in the last section, the network structure affects the speed of product diffusion. Although the AB model is capable of simulating the real purchasing behaviors of individual consumers, its performance may be constrained by the network structure. Since it was impossible to know how real consumers' social network is configured, we investigated 16 different network structures by varying the rewiring constant and the degree of connectivity (i.e. the number of neighbors connected to each consumer), and found the best one with minimum forecasting error. Four rewiring constants (0.05, 0.1, 0.25, 0.5) and four degrees of connectivity (4, 6, 8, 10) were considered in the calibration experiment.

For the expert's product information on the three car models, we used the data that was created by the expert group of a famous car magazine. The data have been accessible through the web site of the car magazine company. The performance ratings of the car models with respect to nine attributes are shown in Table 2. From the table, we could make two observations. First, the expert group concluded that the model C3 was superior to the others in all aspects except brand preference and price. Second, as for the models C1 and C2, the expert group gave similar ratings to the nine attributes. Only from what is in the data, it is not easy to predict which car will be the winner in the market.

We performed a survey with 400 potential consumers for estimating individual consumers' weights on the nine attributes and

Table 2
Product information created by an expert group.

Model	Attribute								
	Brand preference	Price	Acceleration	Safety	Fuel economy	Exterior	Interior	Convenience equipment	Comfort
C1	G	G	E	VG	F	VG	VG	E	VG
C2	G	G	VG	G	F	VG	E	VG	E
C3	F	F	E	E	G	E	E	E	E

sensitivity level to social influence. The survey results are summarized in Tables 3 and 4. From Table 3, we could find that a large portion of the respondents gave more emphasis on the price attribute – 73% of the respondents assigned "high" and "very high" grades to the attribute, while, on average, 46% of them gave the same grades to the other attributes. The result in Table 4 shows that 65% of the respondents were (normally, strongly, or very strongly) sensitive to social influence. In the AB model, the weights and the sensitivity level to social influence were randomly given to each consumer-agent by using the relative frequency distributions estimated from the survey results.

We used Netlogo (Wilensky, 1999), one of representative multi-agent tools, to implement the AB model. We considered small-world networks of 10,000 consumer-agents. The time unit of the agent-based diffusion was a month. To harmonize the release timings of the three car models in the AB model with reality, we started the diffusion of C1 and C2 at time zero and introduced C3 at the 19th month.

Table 4
Consumers' sensitivity level to social influence.

Sensitivity level	Respondents	Relative frequency
Very strong	87	0.22
Strong	75	0.19
Normal	96	0.24
Weak	67	0.17
Very weak	75	0.19

Table 5
Result of calibration experiment.

Number of neighbors	Total mean market-share error Rewiring constant			
	0.05	0.1	0.25	0.5
4	2.65%	**2.61%** (min)	2.63%	2.66%
6	2.83%	2.79%	2.91%	2.91%
8	2.77%	2.86%	2.85%	2.89%
10	**2.92%** (max)	2.84%	2.91%	2.74%
Average	2.79%			

4. Results and discussion

The monthly sales volumes of the three car models were collected over 38 months (June, 2006–August, 2009), which were used for the calibration experiment. Table 5 shows the result of the calibration experiment. The performance measure was total mean market-share error, which was calculated by averaging the mean market-share errors of the three car models. For an execution result, the mean market-share error of a car model was obtained using

$$\text{Mean market-share error} = \frac{\sum |\text{monthly difference between model data and real data}|}{\text{total number of months}} \tag{10}$$

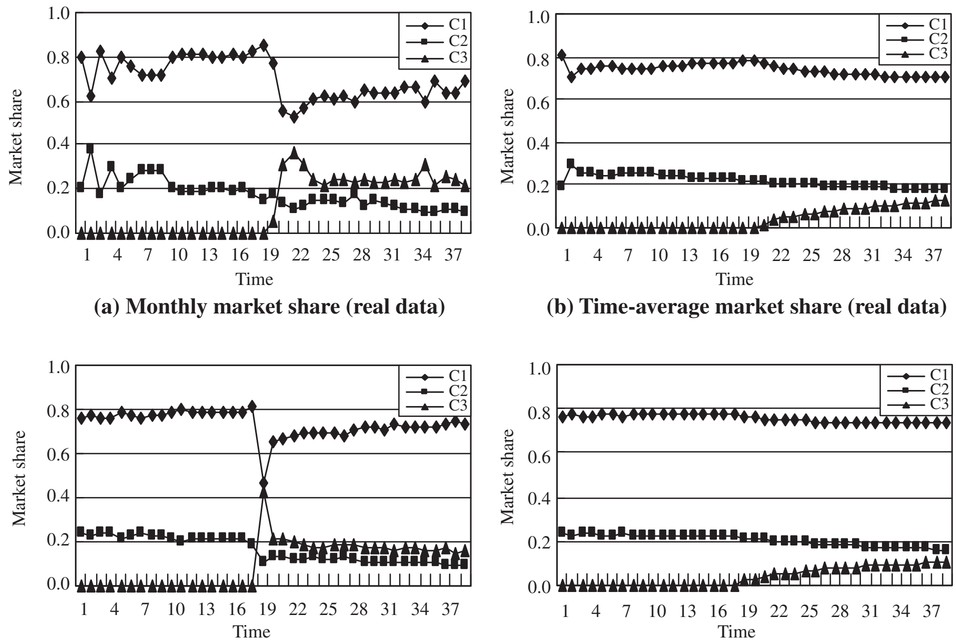
In order to obtain a statistically reliable measure which is in 95% statistical confidence interval, we executed the AB model eight times for a given network structure (Law, 2006) and averaged the obtained total mean market-share errors.

As shown in Table 5, the maximum and minimum of the total mean market-share errors were 2.61% and 2.92%, respectively. The minimum error was obtained when the rewiring constant and the degree of connectivity were set to 0.1 and 4, respectively, while the maximum error was obtained when those parameters were set to 0.05 and 10, respectively. The average error of the 16 network structures was 2.79%. From the result, it was found that, within this empirical study, the network structure little affected the diffusion of the three car models. The reason may be due to the consumer-agents' preference of C1 over C2 and C3. As shown in Fig. 1(a), C1 has dominated C3 in the real market because C1 has price advantage over C3 and consumers were very sensitive to the price of car (see Table 3). In addition, C1 is more competitive than C2 with regard to three attributes of acceleration, safety, and convenience equipment, while C2 has advantage over C1 regarding two attributes of interior and comfort (see Table 2). As the result, the early adopters in the AB model had a strong tendency to prefer C1 to C2 and C3, which provides feedback to non-adopters and affected their purchase decisions (i.e., social influence). The preference tendency seemed to change little regardless of the diffusion speed which is determined by the two network parameters. Therefore, the 16 network structures made similar diffusion results. So did the errors.

Fig. 1(a) shows the monthly market shares of the three car models where the monthly market share of each product is defined as the monthly sales volume of the product over the total monthly sales volume. Fig. 1(b) shows the time-average market shares of those models. As the two graphs indicate, C1 has kept a dominant position in sales over the others. However, as C3 was announced,

Table 3
Consumers' weights on nine attributes.

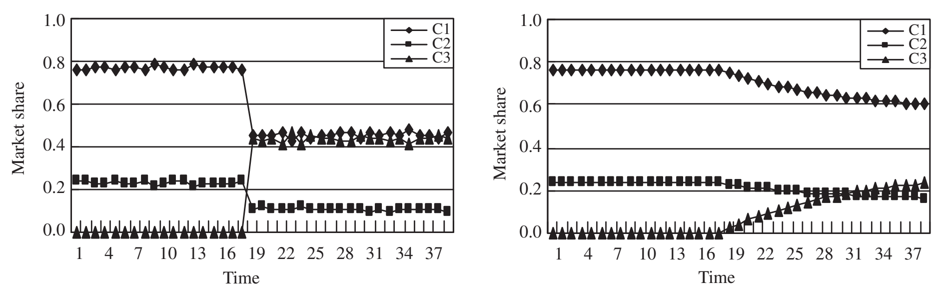
Weight	Attribute								
	Brand preference	Price	Acceleration	Safety	Fuel economy	Exterior	Interior	Convenience equipment	Comfort
Very low	32 (0.08)	20 (0.05)	68 (0.17)	75 (0.19)	76 (0.19)	41 (0.10)	79 (0.20)	45 (0.11)	67 (0.17)
Low	49 (0.12)	32 (0.08)	97 (0.24)	68 (0.17)	64 (0.16)	75 (0.19)	75 (0.19)	69 (0.17)	49 (0.12)
Medium	86 (0.22)	55 (0.14)	87 (0.22)	91 (0.23)	80 (0.20)	98 (0.25)	88 (0.22)	85 (0.21)	76 (0.19)
High	101 (0.23)	110 (0.27)	76 (0.19)	112 (0.28)	94 (0.24)	108 (0.27)	72 (0.18)	97 (0.24)	94 (0.24)
Very high	132 (0.33)	183 (0.46)	72 (0.18)	54 (0.14)	86 (0.21)	78 (0.20)	86 (0.22)	104 (0.26)	114 (0.29)



(a) Monthly market share (real data) (b) Time-average market share (real data)

(c) Monthly market share (model data) (d) Time-average market share (model data)

Fig. 1. Comparison between real data and model data.



(a) Monthly market share (model data) (b) Time-average market share (model data)

Fig. 2. Model data without social influence.

C1 suffered from a strong erosion by C3 for a while, but C1 has begun to recover its market share after the erosion (see Fig. 1(a)). Whereas, the market share of C2 has decreased gradually due to the introduction of C3. Fig. 1(c) and (d) shows the diffusion paths of the three car models created by the AB model when the network was configured with the rewiring constant of 0.1 and the degree of connectivity of 4. In Fig. 1(c), the monthly market shares of the AB model could not reflect the random variations made in realty as shown in Fig. 1(a). This is because the fuzzy TOPSIS-based product adoption process does not consider the uncertainties in human's decisions making. In the real situation, some of the consumers would have not behaved like rational decision makers. Whereas, the AB model assumed all consumer-agents to be rational; the consumer-agents selected the best ones considering both their personalized product ratings and the social influence that they received from neighbors. However, the AB model was able to forecast the overall trends of the monthly market shares of the three car models. The total mean market-share error was 7.37%. In addition, we obtained a meaningful result when we evaluated the performance of the AB model from the aspect of the time-average measure which is known to smooth the random variations. The time-average market shares of the three car models in Fig. 1(d) are similar to the real ones in Fig. 1(b). The total mean of the time-average errors of the three car models was 1.44%.

Finally, we considered a diffusion scenario without social influence. For this, the sensitivity levels to social influence of all consumer-agents (α_k) were set to zero and we executed the AB model. Under the scenario, every consumers-agent made purchase decision based on only its own personalized product information. The result is shown in Fig. 2 where C3 absorbed the market share of C1 more than the amount in the real market. The result demonstrated the power of social influence. C1 and C2 have already been sold in the market during 18 months before the introduction of C3. These two car models (C1 and C2) won good reputations from the early adopters and, as the result, a wave of positive word-of-mouth is made. Although C3 was superior to C1 and C2 in almost every aspect, it was difficult for C3 to expand its market share rapidly because of the "lock-in" effect of C1 and C2. If the effect was weak, then, just like in Fig. 2, C3 could have been successful to increase its market share more than the real one.

5. Concluding remarks

In this paper, we proposed the agent-based product diffusion model and applied it to the market of full-sized cars in Korea. Throughout the empirical study, we investigated the performance of the AB model with the sales data obtained in the automobile market. Although the empirical study showed an encouraging result, this is not sufficient to support that the AB model is appropriate for the markets of different types of products. The AB model was developed for forecasting the diffusion of high-priced products with long product life cycles such as cars and high-end TVs. Consumers in other markets probably show different behaviors in purchasing products. For example, consumers in the markets of fashionable goods are likely to mimic actively what their neighbors do. In such case, threshold-based models, in which consumers adopt products when the number of friends who adopt the products exceeds the thresholds of the consumers, may be appropriate. We are currently generalizing the AB model to accommodate the threshold-based product adoption process.

Acknowledgement

This work was supported by the Korea Research Foundation Grant (KRF-2009-013-D00136).

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