Competitive Products' Diffusion Behavior considering Cost Learning Effect Based on System Dynamics

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Abstract — **Bass Model, the most representative accomplishment in the field of product diffusion, is built on a series of assumptions which seriously limit the applied range of the model. This paper improves Bass Model so that it could be applied to competitive products. Also, this paper presents an expression of the analytical form of product margins. By taking the unit variable cost's learning effect into consideration, its impacts on product gains was analyzed and proved theoretically. The traditional mathematical model being utilized to describe the product diffusion procedure was converted into system dynamics model. The validity of the model was proved qualitatively through the simulation by harnessing Vensim software. Besides, sensitivity analysis of variants was conducted to explore the typical parameters and to see in which way they would have influence on the model. Variable analysis and the results of model simulation further reflect the interactions and system structural characteristics of various factors which have a bearing on the product diffusion. The structural properties are thoroughly studied, thus provide a solid base for setting the strategies concerning product development and diffusion process.**

Keywords - ***System dynamics; Product diffusion; Simulation; Modeling; Learning effect***

I. INTRODUCTION

Processing is the procedure of converting raw materials and information into completed commodities with high value added for the satisfaction of human demands [1]. The concept of product diffusion refers to the process of a product being accepted by society, associations and personal consumers after it is manufactured. The research in product diffusion involves diverse fields of studies and has come up with attractive results since the pioneering work of Bass [2]. Nevertheless, the application of Bass model is limited owing to its assumptions of monopoly and durable products. As a matter of fact, the competitiveness is the ultimate goal for each company in the market who devote themselves in maximizing their interests. Technology develops in rapid pace, which contributes to the fact that the development cycle frequently exceeds the new product's market life [3]. The main competitive strength of an enterprise is based on its rapidness of responding to the market and innovative product development technologies [4]. So the competitiveness in the diffusion process has been paid increasing attentions [5]. Some researchers make profits maximization as the ultimate objective when they make decisions concerning product development and diffusion [6]. In the case of the diffusion process of technology-intensive products, the learning effect should be given special attention. The time learning effect is often considered in scheduling problems [7, 8]. This paper attempts to take the cost learning effect in the diffusion process of competitive products into consideration in order to analyze how the learning effect have a bearing on the process of product diffusion and product profits. Since the product diffusion is a complex and dynamical process which consists of various interactions between variables. It is more complicated to think over the competitive situation than just one single product system. And System Dynamics (SD) is more applicable for these intricate systems. Some researchers have applied SD in modeling some supply chain system [9] and manufacturing systems. The simulation software of SD models can be described as an excellent tool for quantitative analysis. This paper aims to construct a competitive product diffusion model to reflect the interrelationships between variants on the basis of SD. Consequently, with using the simulation software to study those results, we are able to capture the dynamic features of product diffusion procedure and offer certain efficacious policies for product management.

II. LITERATURE REVIEW

A diffusion procedure is the propagation of an innovation product from its beginning to the final customer [10]. Because of its significant importance in the area of market, academicians focus more on the study of product diffusion theory [11-14]. Diffusion models, which concern with the new product's promotion, have been paid more attention in marketing research since the precedent achievement of Bass [2]. These models pay attention to the description of the dynamic characteristic of new product promotion. Traditionally, it is considered as durable products, if the first purchase represents a large proportion of total sales in the product's early life cycle. Ever since the pioneering work of Bass, significant extensions and generalizations have appeared based on the fundamental model. Innovations models' diffusion process have been utilized to predict social reactions to different products in general. Shi et al. [15] came up with a parsimonious and original model that captured the dynamics of multi-generational product diffusion in current high-technology markets. Liu et al.[16] studied the optimal time paths of product innovation diffusion model based on game theory. To understand the effect of both pricing and capacity, Shen et al. [17] considered the integrated optimal pricing, production, and inventory decisions, using control-theory framework (a generalization of the classic Bass model). Guo et al.[18] proposed a grey diffusion model based on grey system theory to address the promotion style of new products and the characteristics of a small sample. In order to help managers make reliable predictions of the respective innovation diffusion process, Stummer et al. [19] introduced an agent-based model that dealt with repeat purchase decisions, addressed the competitive diffusion of multiple products, and took into consideration both the temporal and the spatial dimension of innovation diffusion. Whatever great achievements have been made in this research field, making profits is the final goal of enterprises. The combination of learning effect of variable cost with product diffusion would be invaluable for the enterprises.

III. SYSTEM MODELING

Currently, diffusion models are built based on Bass model, which is a second-order system with two cumulative variables: potential customers and actual adopters. It assumes additional adopters are consist of innovators and imitators during a period of time. Innovators refer to the group, which is affected by the advertising media to adopt the product; imitators refer to the group which accepts the product because of the communication with adopters.

3.1 BASS MODEL

Bass model assumes that there is only one single product in the market, which indicates that it is a monopoly one. In addition, the product can be used continuously for a long period if it is durable, which means that an individual or a whole family will need only one of them. Thus, the number of the product sales roughly is equivalent to the number of consumers using the product. Furthermore, Bass model supposes that additional adopters including innovators and imitators in a period are described by two factors, the interior factor (denoted by p , named as innovation coefficient) and the exterior factor (denoted by q , named as imitation coefficient).

The Bass model can be described as (1), and the corresponding system dynamics model is shown in Figure 1.

$$dN(t)/dt = p(M - N(t)) + qN(t)(1 - N(t)/M) \quad (1)$$

where

$N(t)$: the adopters of the product;

M : the whole market share;

p : the innovation coefficient;

q : the imitation coefficient.

Then we gain the analytical solutions of this differential equation, which are shown in (2)-(3). The solutions demonstrate that the increasing trend of adopters depicts an S-curve, while the increasing rate exhibits a bell-shaped curve (as shown in Figure 2).

$$N(t) = M(1 - e^{-(p+q)t})/(q/pe^{-(p+q)t} + 1) \quad (2)$$

$$dN(t)/dt = M((p+q)^2/p)[e^{-(p+q)t}/(q/pe^{-(p+q)t} + 1)^2] \quad (3)$$

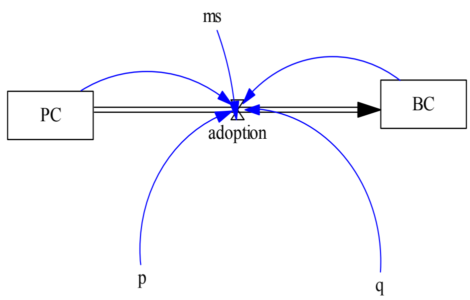

Figure 1. Bass model

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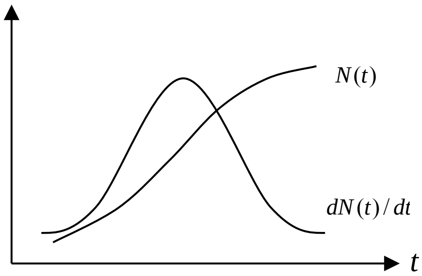

Figure 2. The solution of Bass model

Dynamo equations for Bass model:
BC(t)=BC(t-dt)+(adoption)*dt;
INIT BC=0;
Adoption=PC*p+PC*BC/ms*q;
PC(t)=PC(t-dt)+(-adoption)*dt;
INIT PC=10000
ms=10000
p=0.01
q=1;
where:
BC: number of current adopters;
Adoption: users increased per season;
INIT BC: initial customers;
PC: number of potential customers;
ms: market scale;
p: innovation coefficient;
q: imitation coefficient.

3.2 COMPETITIVE DIFFUSION BASED ON CONSTANT UNIT VARIABLE COST

TABLE 1. DENOTATIONS

$Grav_A(t)$	The Market gravitation of product A
$Grav_B(t)$	The Market gravitation of product B
$N_A(t)$	Number of adopters of product A
$N_B(t)$	Number of adopters of product B
$N(t)$	Number of adopters of similar products
P_A	Price of product A
P_B	Price of product B
FC_A	Fixed cost of product A
FC_B	Fixed cost of product B
UVC_A	Unit variable cost of product A
UVC_B	Unit variable cost of product B
$R_A(t)$	Profits of product A
$R_B(t)$	Profits of product B

The facts that products have competitors do not satisfy the single product hypothesis of the Bass model. Imagine that there are two enterprises producing product A and B respectively. Both enterprises remain independent to set up the price for their products which approximately share same quality. Based on these conditions, the price will have an impact on the market share, thus affects the ultimate income. The lower-pricing enterprise would be more competitive and acquire more market share, thus, earn more margins. In order to make things simple, we assume that the market share of every product correlates solely to the product's price. Then we have the following definitions on the base of the parameters denoted in Table 1.

Definition 1 Market gravitation ($Grav$) refers to the market occupancy of a product, which is denoted as the percentage of a product's market share, namely:

$$Market\ gravigation = \frac{Market\ sales}{Total\ market\ sales\ of\ similar\ products} \times 1 \tag{4}$$

Thus the market gravitation of product A is:

$$Grav_A = \frac{N_A(t)}{N_A(t) + N_B(t)} \times 100\% \tag{5}$$

It negatively correlates to the price of products, i.e. the product with higher price has lower market gravitation. So we set

$$Grav_A(t) = P_B / (P_A + P_B)\ . \tag{6}$$

We put forward that the diffusion of the total sales of similar products is in accordance with Bass model. Thus we

$$N_A(t) = Grav_A(t) \cdot N(t)$$
$$= [P_B / (P_A + P_B)] \cdot M(1 - e^{-(p+q)t}) / (q / pe^{-(p+q)t} + 1)\ . \tag{7}$$

Given that unit variable cost is fixed, the earnings of product A is

$$R_A(t) = P_A \cdot N_A(t) - FC_A - UVC_A N_A(t)$$
$$= [P_A P_B / (P_A + P_B)] \cdot M(1 - e^{-(p+q)t}) / (q / pe^{-(p+q)t} + 1)$$
$$- FC_A - UVC_A \cdot [P_B / (P_A + P_B)] \cdot$$
$$M(1 - e^{-(p+q)t}) / (q / pe^{-(p+q)t} + 1) \tag{8}$$

Likewise, the profits of product B is

$$R_B(t) = P_B \cdot N_B(t) - FC_B - UVC_B N_B(t)$$

$$=[P_A P_B/(P_A+P_B)]\cdot M(1-e^{-(p+q)t})/(q/pe^{-(p+q)t}+1)$$
$$-FC_B-UVC_B\cdot[P_A/(P_A+P_B)]\cdot$$
$$M(1-e^{-(p+q)t})/(q/pe^{-(p+q)t}+1) \quad (9)$$

So if the unit variable cost of each product is settled, the profit difference between diverse products would depend on the fixed cost, the unit variable cost and the price of each product. It is obvious that if both products share the same price and same cost, they are supposed to have the same market gravitation and the same profits. Nonetheless, with respect to newly developed products, especially the technology intensive ones, there is an evident learning effect on the variable cost. The product margins are not able to be described by Eqs. 8, 9.

3.3 Competitive Diffusion with Cost Learning Effect of Unit Variable Cost

Herein before we supposed that the unit variable cost was constant. However, the long-run average cost decreases as the experience of workers, technicians and managers as well as technological design, management and so on accumulated [20]. This is called "learning effect". The trend is displayed as "learning curve". The truth is, the unit variable cost has a learning effect other than being fixed, especially for certain newly developed products. So the unit variable cost is expressed as:

$$UVC(N)=UVC(1)\cdot N^{-a} \quad (10)$$

where $UVC(N)$ is the unit variable cost of the Nth product;

N is number of a product' s cumulative adopters;

$-a$ is the learning index of cost with respect to the production.

According to the learning effect theory, learning rate, which is represented as δ, refers to the rate to which the manufacturing cost or time decreased when the production doubled. The learning rate varies with the differences of the producing complexity. In general, the learning rate of a new product ranges from 70% to 95%.

From the definition of learning rate, we have

$$\delta=UVC(2N)/UVC(N)$$
$$=[UVC(1)(2N)^{-a}]/[UVC(1)N^{-a}]=2^{-a}$$

Thus $a=-\log_2\delta$, and a approximately ranges from 0.07 to 0.5.

Proposition 1 We assume that product A is an emerging product, which has a learning effect on unit variable cost. As for product B, we suppose it is a mature product without regard to learning effect. Both products have the same fixed cost and price, the critical point of $N(t)$ where product A and product B would have equal profits is $N(t)=2\{UVC_A/[(1-a)\cdot UVC_B]\}^{1/a}$.

Proof The profits of product A is

$$R_A(t)=P_A N_A(t)-FC_A-\int UVC(N_A)dN_A$$
$$=P_A N_A-FC_A-\int(UVC_A(1)\cdot N_A(t)^{-a})dN_A(t)$$
$$=P_A N_A(t)-FC_A-UVC_A(1)\cdot N_A^{1-a}(t)/(1-a)$$
$$=[P_A P_B/(P_A+P_B)]\cdot M(1-e^{-(p+q)t})/(q/pe^{-(p+q)t}+1)-$$
$$FC_A-UVC_A(1)\cdot[P_B/(P_A+P_B)]$$
$$\cdot M\cdot(1-e^{-(p+q)t})/[(1-a)\cdot(q/pe^{-(p+q)t}+1)^{1-a}] \quad (11)$$

If both products have the same price ($P_A=P_B=P$) and the same settled cost ($FC_A=FC_B=FC$), product B has the constant unit variable cost. From Eqs.9 and 11, we obtain the disparity between the interests of two products

$$R_A(t)-R_B(t)=UVC_B\cdot M(1-e^{-(p+q)t})/[2(q/pe^{-(p+q)t}+1)]$$
$$-UVC_A(1)\cdot M\cdot(1-e^{-(p+q)t})/[2(1-a)\cdot(q/pe^{-(p+q)t}+1)^{1-a}]$$
$$=UVC_B\cdot N(t)/2-UVC_A(1)\cdot[N(t)/2]^{1-a}/(1-a)$$
$$=N(t)/2\cdot\{UVC_B-UVC_A(1)\cdot[N(t)/2]^{-a}/(1-a)\}, \quad (12)$$

where $N(t)>0, 1-a>0$.

If $N(t)>2\{UVC_A/[(1-a)\cdot UVC_B]\}^{1/a}$, then $R_A(t)-R_B(t)>0$, and product A would gain more profits from the market, and vice versa. So $N(t)=2\{UVC_A/[(1-a)\cdot UVC_B]\}^{1/a}$ is the critical point where product A and B share the equal profits. The proof of Proposition 1 is completed.

Corollary1 $M>2\{UVC_A/[(1-a)\cdot UVC_B]\}^{1/a}$ is a necessity that product A eventually gains more profits than B does.

Proof. From Eq. (11) and proposition1, we know that if $R_A(t)-R_B(t)>0$, then $N(t)>2\{UVC_A/[(1-a)\cdot UVC_B]\}^{1/a}$, and

$$\lim N(t)>\lim 2\{UVC_A/[(1-a)\cdot UVC_B]\}^{1/a} \quad (13)$$

hence

$$\lim_{t\to\infty}N(t)=\lim_{t\to\infty}[M(1-e^{-(p+q)t})/(q/pe^{-(p+q)t}+1)]=M. \quad (14)$$

Therefore, only if $M>2\{UVC_A/[(1-a)\cdot UVC_B]\}^{1/a}$, could it be possible that product A would gain more benefits from the market in the lone run. This completes the proof.

Thus it is safe to conclude that:

i. The newly developed product has higher unit variable cost at the initial period of its life cycle. However if it has a dominant learning effect, it is able to obtain more profits from the market ultimately.

ii. It is pivotal to take market scale into consideration. When the size of market is small, the newly developed product only gains little margins from its learning effect. In the next section, we tend to set up a simulation model to further verify the above mentioned results.

IV. Model Simulation and Analysis

We assume that there are two products existing in the market that share similar functions and performance. The two enterprises are able to set the price for their products separately. In order to compete for the profits, the two companies implement the policy that set the same price along with each one. Product A is a emerging product and it owns a high unit variable cost at its prior period of life. The enterprise gives priority to the training of its workers. Thus, the unit variable cost exhibits a strong trend of learning curve. We establish a simulation model of the the two products' competitive diffusion model as shown in Figure 3.

In the following section we attempt to run the above model in different conditions, through which we obtain the dynamic features of the system. Respectively, we establish fundamental simulation and sensitivity analysis. By running fundamental simulation, we gain the system behavior and the varying trends of main variables. Moreover, the sensitivity analysis reveals the real consequence of the system organization. In the fundamental simulation, we first give the unit variable cost of product A and B the same value, and make the learning index=0. This indicates both products do not have learning effect, then we change the parameters to carry on sensitivity analyses.

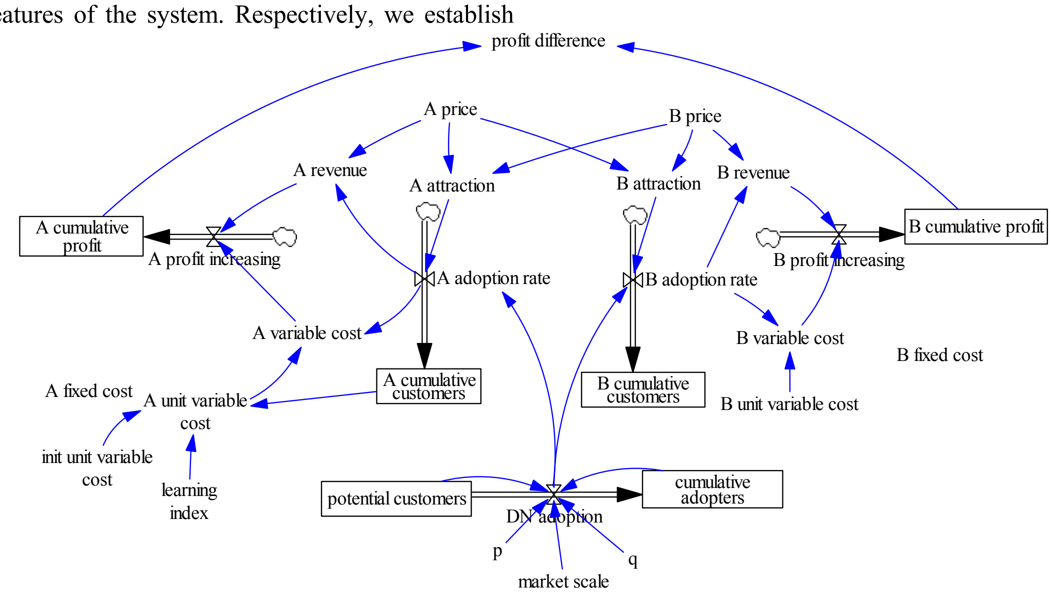

Figure 3. Two products diffusion model

Dynamo equations for two products diffusion model:

A gravitation=B price/(B price+A price);

Aadoption rate=DN adoption * A gravitation;

Acumulative customers(t)=A cumulative customers（t-dt）+A adoption rate*dt;

INIT A cumulative customers=1;

A unit variable cost= init unit variable cost*Power(A cumulative customers,learning index);

A variable cost=A unit variable cost*A adoption rate;

A revenue=A adoption rate*A price;

A profit increasing=A revenue-A variable cost;

Acumulative profit(t)= A cumulative profit(t-dt) +A profit increasing*dt;

INIT A cumulative profit = -A fixed cost

B gravitation=A price/(B price+A price);

B adoption rate=DN adoption * B gravitation;

B cumulative customers(t)=B cumulative customers（t-dt）+B adoption rate*dt;

INIT B cumulative customers=0;

B variable cost=B unit variable cost*B adoption rate;

B revenue=B adoption rate*B price;

B profit increasing=B revenue-B variable cost;

B cumulative profit(t)= B cumulative profit(t-dt) +B profit increasing*dt;

INIT B cumulative profit = -B fixed cost

potential customers(t)= potential customers(t-dt)+(-DN adoption)*dt;

INIT potential custome s= market scale;

cumulativeadopters(t)=cumulative adopters(t-dt)+ DN adoption*dt;

INIT cumulative adopters=0;

Cumulative adopters=potential customers*p+ potential customers*cumulative adopters/market scale*q;

A fixed cost=50000

B fixed cost=50000;

init unit variable cost=200;

B unit variable cost=200;

A price=4000;

Bprice=4000;

p=0.005;

q=0.5;

learning index=0;

Market scale=100000.

4.1 Fundamental simulation

We make A unit variable cost = B unit variable cost = 200, learning index=0.After running the model shown in

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Figure 3, and then we get the trend of variables during the process of product diffusion as shown in Figure 4 (trend of potential customers, actual consumers and the adoption rate in (a); trend of accumulative profits and revenue in (b).) The total adopters of similar products A and B would diffuse as the Bass mode. The curve of total adopters is in form of 'S'. In the case of the increasing rate, intuitively being considered as the product sales in a specific stage, displays a bell-shaped graph. The fixed cost is constant while the revenue differs along with the product sales. Given that we set learning index to 0, and the value of unit variable cost is also settled. Therefore, the variable cost in a particular stage varies in direct proportion to the product sales. Both product A and B share the same market gravitation, market share, revenue and profits.

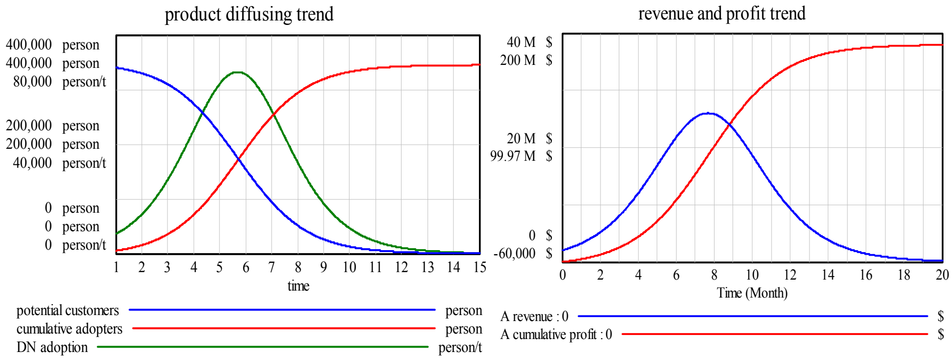
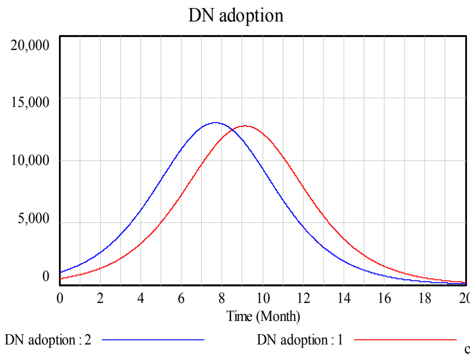


Figure 4. Trend of main variables

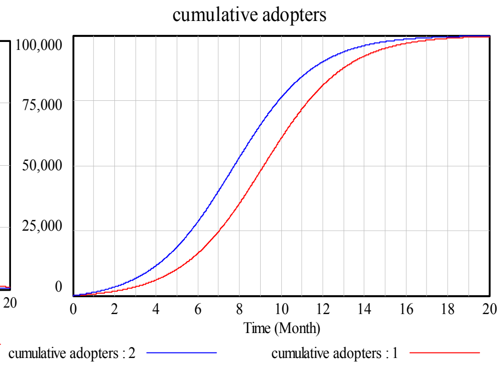
4.2 Sensitivity analysis of innovation coefficient and imitation coefficient

We replace the general marketing conditions with innovation coefficient p and imitation coefficient q. Since q=0.5 and the innovation coefficient p changes from 0.005 to 0.01,both graphs of diffusion rate and cumulative customers move to the left a little. Besides, the values of maximal diffusion rate are almost same (see Figure 5 (a), (b)). It indicates that the variation of p changes the life cycle of product adoption, but it does not significantly affect the peak value of product diffusion rate.

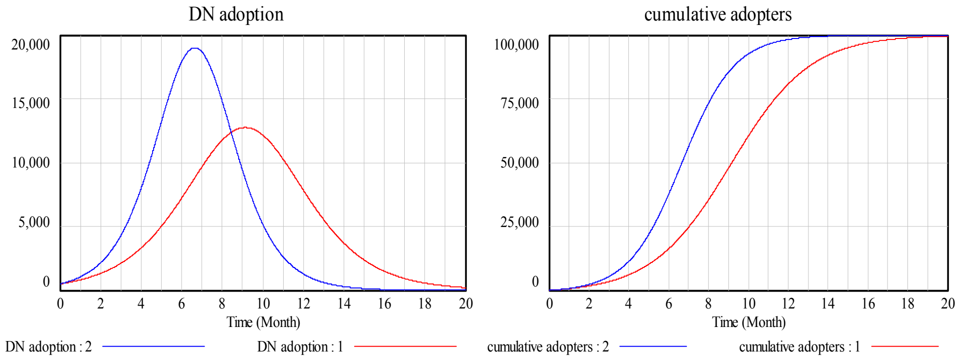
Nonetheless, given that p=0.005 and the imitation coefficient varies from 0.5 to 0.75.The time needed to reach the peak sales is shortened and the maximum value of diffusion rate raises (see Figure 5 (c), (d)). So it is safe to conclude that the more frequent communication between adopters and non-adopters not only reduces the time of life cycle but also enhances the diffusion rate.



(a) Sensitivity of adoption rate to p



(b) Sensitivity of cumulative adopters to p



(c) Sensitivity of adoption rate to q

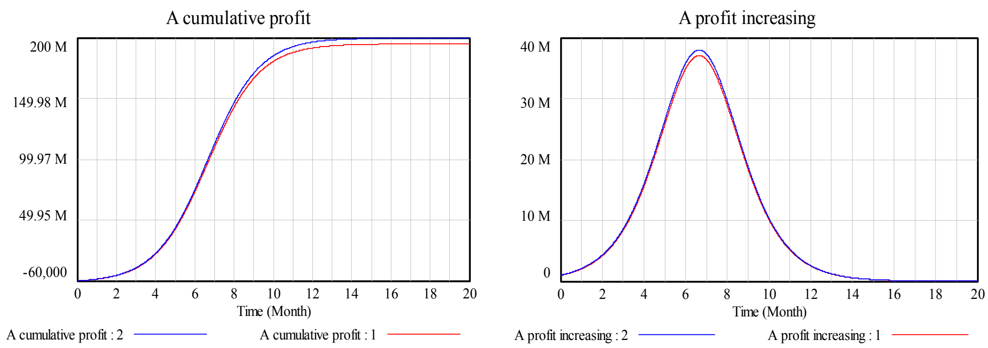
(d) Sensitivity of cumulative adopters to q

Figure 5. Sensitivity to innovation and imitation coefficient

This is because the disparity of magnitude orders between innovation coefficient and imitation coefficient. After forecasting more than ten types of products' diffusion behavior and their parameters, Bass concludes that p is much less than q [2]. Despite increasing both p and q would accelerate the diffusion rate, the influence of the former factor cannot be observed easily due to its small order of magnitude, yet the influence on the latter factor is much more significant.

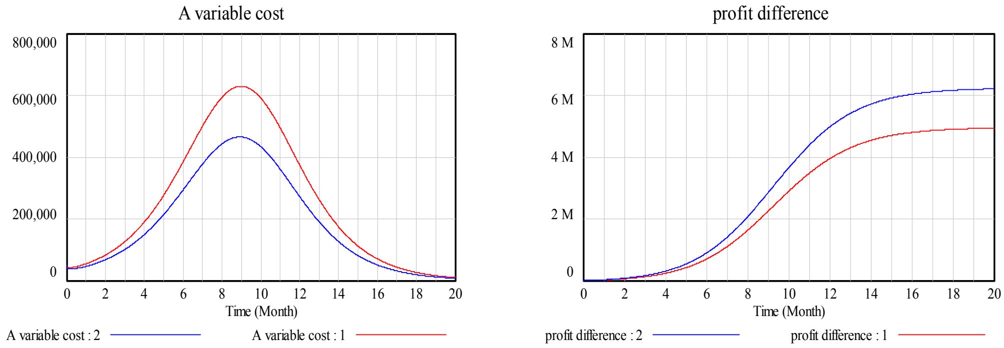
As is demonstrated in the learning effect theory, if product A is a newly developed product, the unit variable cost would diminishes when the workers accumulate more manufacturing experience and become more skillful. Given that initial unit variable cost of A is 300 and unit variable cost of B is 200, the following sections illustrate that how sensitive the variables would be to learning index when it varies from -0.07 to -0.1.

4.3 Sensitivity analysis of the learning effect coefficient



(a)Sensitivity of cumulative profits to learning index

(b) Sensitivity of profit increasing to learning index



(c)Sensitivity of variable cost to learning index (d) Sensitivity of profit difference to learning index

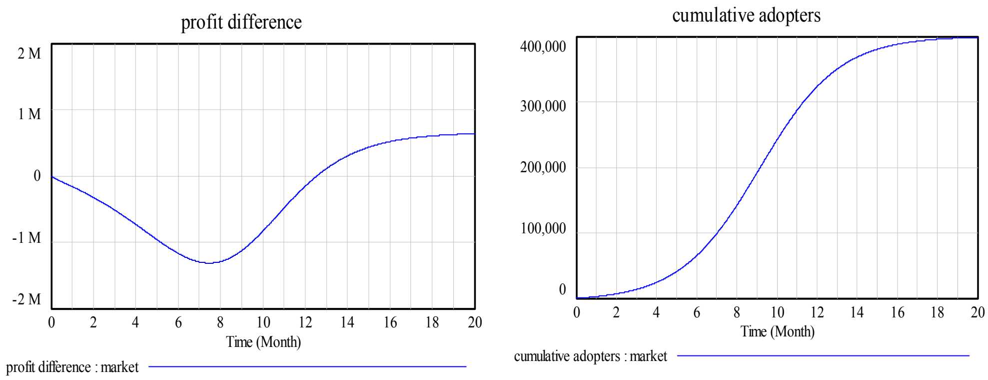
Figure 6. Sensitivity to learning index

It is easy to find that when there is a stronger learning effect, the product get more profits. The learning effect actually have certain impacts on the profits, even if it cannot be clearly observed from the charts. Therefore, we draw the following conclusion that the product increasing and accumulative profits are not sensitive to the learning index (see Figure 6 (a), (b)). The reason is that the variable cost has a much smaller value comparing to the income of the product, also, the unit variable cost would not decrease unlimitedly. Instead, it descends to a lower bound and then keep stable at that position.

The variable cost and profit difference are very sensitive to the learning index (see Figure 6 (c), (d)). When the mean value of learning index raises, the variable cost decreases rapidly. In the earlier period of its diffusion, due to the product A's higher unit variable cost, the margin of product A is less than that of product B, thus the profit difference is negative. When the learning effect works, the unit variable cost of product A declines, so the profit difference becomes positive. The mean of learning index's increase expands the interests difference between product A and B.

4.4 The influence of market scale on product profits

We need to testify the conclusion of Proposition 1 and Inference 1 by simulation, i.e. to observe the profit difference of product A and B near critical point. In the previous stage of simulation, we set the initial value of unit variable cost of A $UCV_A(1)=300$. According to Proposition 1, if $a=0.1$, then the critical point where A and B have equal profits is $N(t)=331$, which is far less than the market scale $M=100000$. Therefore the long-term simulation results are not easily observed. We modify $UCV_A(1)$ to 600 and M to 400000 for convenience sake. From Proposition 1, we deduce that the critical point of equal profits is $N(t)=338702$, which is consistent with simulation results displayed in Figure 7 (a), (b).



(a) The influence of market scale on profit difference (b)The influence of market scale on cumulative adopters

Figure 7. The influence of market scale

4.5 The diffusion of consumable products

In the previous model, only the competitive diffusion behavior of durable products was taken into account. In the reality of marketing, there are many consumable products like daily commodities whose diffusion process do not accord with Bass mode. In their diffusion processes, the customers need to purchase new products repetitively to meet daily requirements, as the consumption of products is continuous. These products have relatively long life cycle to display the influence of learning effect. The difference between these products and durable products is that the influence of learning effect on their unit variable cost does not rely on the number of adopters but on cumulative production. In our study, we consider one consumable product for simplicity. Because a percentage of products would be consumed at any stage, the diffusion process differed from Bass mode. These corresponding customers become potential customers again after their products are expended. The products are manufactured continuously and the learning effect is well displayed.

The percentage of expended is denoted as expending rate which is set to 0.075 in the simulation model. The diffusion model for consumable products is given in Figure 8. The simulation results show that the diffusion process is similar to Bass mode during the early stage. After more products reach their life span they are repurchased by customers. When the model goes stable, the sales and consumption keep constant (Figure 9 (a), (b)). The unit variable cost decreases at first and then become constant due to learning effect. The cumulative profits raise slowly at first, and then grow faster, and increase steadily at last(Figure 9 (c), (d)).

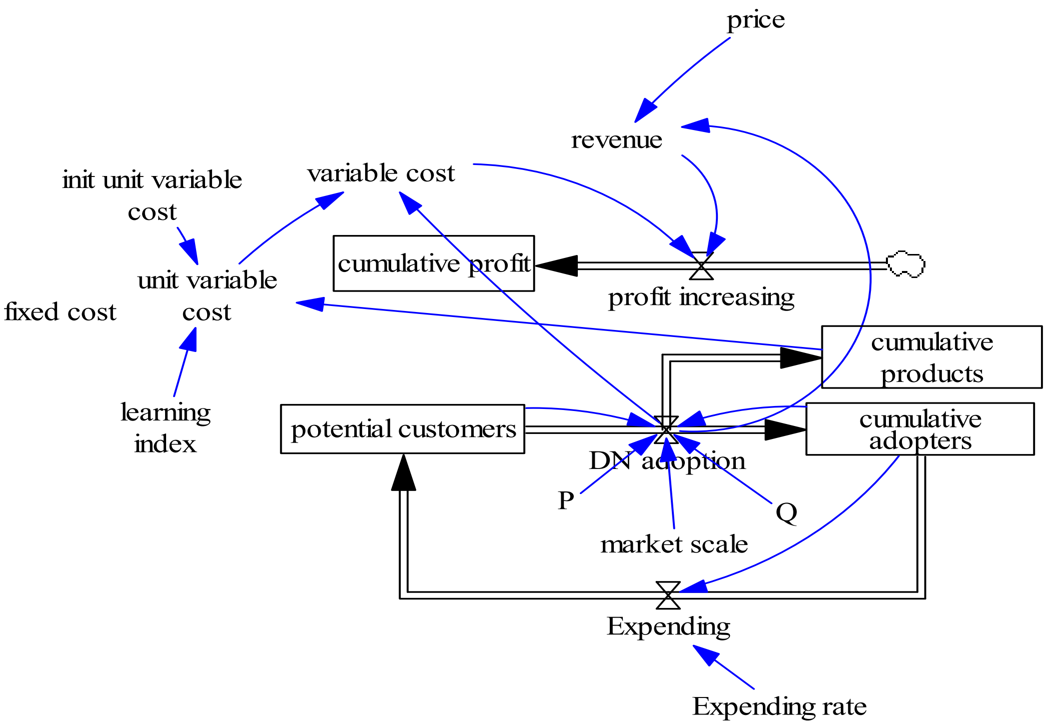
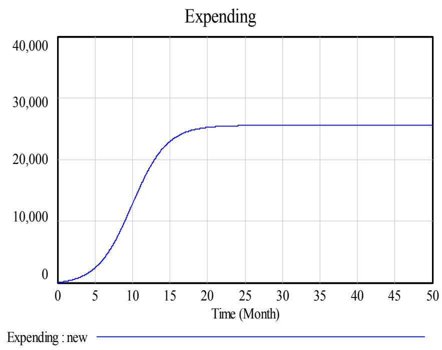


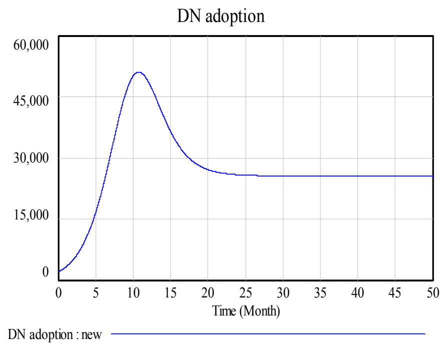
Figure 8. Diffusion model of consumable products

Dynamo equations for consumable products diffusion model:

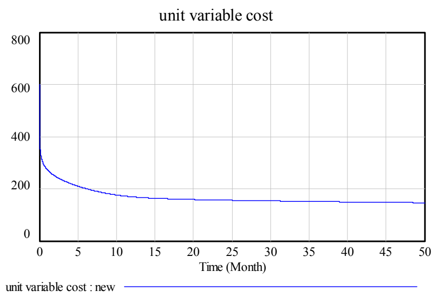
init unit variable cost=600;
fixed cost=5000;
learning index=0.1;
P=0.005;
Q=0.5;
market scale=400000;
Expending rate=0.075;
Expending=Expending rate*cumulative adopters;
cumulative products(t)=cumulative products(t-dt)+DN adoption*dt;
INIT cumulative products=1;
cumulative adopters(t)=cumulative adopters(t-dt)+ DN adoption*dt-Expending*dt;
INIT cumulative product=0;
potential customers=potential customers(t-dt)+Expending*dt-DN adoption*dt;
INIT potential customers=market scale;
DN adoption=potential customers*P+potential customers*cumulative adopters/market scale*Q;
price=4000;
revenue=DN adoption*price;
profit increasing=revenue-variable cost;
cumulative profit=cumulative profit(t-dt)+ profit increasing*dt;
INIT cumulative profit=-fixed cost;
unit variable cost=init unit variable cost*Power(cumulative products, learning index);
variable cost=unit variable cost*DN adoption.



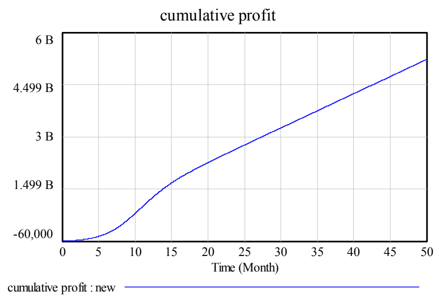
(a)Trend of product expending



(b) Trend of adoption rate



(c) Trend of unit variable cost



(d) Trend of cumulative profits

Figure 9. Learning effect on consumable products

V. CONCLUSIONS

This paper aims to take the learning effect into account to analyze the product diffusion process. Simulation results illustrate that the learning effect has a direct influence on margins, and the market scale determines whether new developed products gain competitive edges with learning effect. The system model is proved to have some practical significance. Reasonable structure and parameters realize the expectant diffusion process. Besides, it is clear that the learning effect have certain impacts on the product profits. Therefore, we can utilize the model to conduct and boost the development of our market strategy.

To keep things simple, we suppose that the diffusion of the two products is in accordance with the same Bass model. Based on this assumption, we are able to infer in which way will the coefficients and learning index affect the system behavior. In fact, the two products have significantly different diffusion modes as well as diffusion processes. Also, product profits are affected by a myriad of other factors, such as advertisement, delivery time, product quality, product brand and so forth. These factors have an influence on the whole market gravitation system and the product diffusion system, which will extend our future science research.

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