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Multigeneration diffusion model for economic assessment of new technology

So Young Sohn[a,*], Byung Joo Ahn[b]

[a]Department of Computer Science and Industrial Systems Engineering, Yonsei University, 134, Shichondong-dong, Sudaemoon-ku, Seoul 120-749, South Korea
[b]J. Walter Tompson, Seoul, South Korea

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Abstract

In the era of 21st century, development of emerging information technology is the essence of the advancement. This kind of new technology, however, often requires a great deal of amount of initial investment for both procedures of R&D and commercialization. As cost invested in developing the specified technology is increasing, investors are paying more attention to cost to benefit analysis (CBA). One of the basic elements of CBA for new technological development is the diffusion pattern of demand of such technology. Typically, it would be hard to presume the diffusion pattern of demand when the new product or the technology is under development. In this case, a simulation study is necessary. Many studies of technology evaluation have adopted a single generation model to simulate the diffusion pattern of demand. This approach, however, considers the diffusion of the new technology itself, not taking into account newer generation, which can replace the one just invented. In the real market situation, one must consider the competition and substitution phenomena between old and new technologies. In this paper, we show how multigeneration technology diffusion model can be applied for more accurate CBA for information technology. Additionally, Monte Carlo simulation is performed to find influential factors on the CBA of a cybernetic building system (CBS).

Keywords: Technology forecasting; Cybernetic building system; Cost benefit analysis; Diffusion model; Monte Carlo simulation; Taguchi design

* Corresponding author. Tel.: +82-2-2123-4014; fax: +82-2-364-7807.
E-mail address: sohns@yonsei.ac.kr (S.Y. Sohn).

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1. Introduction

In the era of 21st century, development of emerging information technology is the essence of the advancement. However, this kind of new technology open requires a great deal of amount of initial investment for both R&D and commercialization. As cost invested in developing the specified technology is increasing, investors are paying more attention to the cost benefit analysis (CBA).

Many researchers have studied the attributes for CBA. In order to evaluate the Energy-Related Inventions Program (ERIP), one of the longest-running commercialization assistance programs in the USA, Brown [1,2] and Brown and Rizy [3] used four performance metrics: (1) the market entry of new products, (2) commercial sales, (3) energy savings, and (4) greenhouse gas emissions reductions. The methodology used to estimate each metric is described, and the strengths and weaknesses of the metrics are discussed.

Kayal [4] evaluated the Technology Cycle Time indicator (TCT), a newly developed objective measure of the pace of technological progress. The TCT indicator was used (1) to assess the pace of progress of superconductor and semiconductor technologies and (2) to assess the position of various countries patenting in the semiconductor technology field. The findings revealed that the TCT provided a valid assessment in each situation. The TCT has important implications for technology management and technology forecasting research.

Watts and Porter [5] studied technological forecasting using bibliometric method. They glean a number of concepts from various innovation models, and then presented an array of bibliometric measures that offer the promise of operationalizing these concepts. Judicious combination of such bibliometric with other forms of evidence offers an enriched form of technological forecasting. This provides a good means to combine technological trends, mapping of technological interdependencies, and competitive intelligence to produce a viable forecast [6–10]. Like this, much research of technological forecasting presented the importance of finding the pattern of demand diffusion over time [11–28].

One of the basic elements of CBA for new technological development would be forecasting the diffusion pattern of such technology. Typically, it would be hard to presume the diffusion pattern of demand when the new product or the technology is under development. For some cases, a technology would penetrate the market quickly, whereas the demand of other kinds of technology would increase slowly in the beginning. Additionally, there are lots of uncertainties involved in external elements such as the characteristics of the market and the customer traits. Due to such difficulty of forecasting, typically, a diffusion model is simulated based on several scenarios. Many studies of technology evaluation have adopted the Mansfield [11,12] model to simulate the diffusion. Recently, Chapman [13] forecasted the sales of cybernetic building system (CBS) technology using the Mansfield model to estimate its economic benefit. The Mansfield model, however, considers the diffusion of the new technology itself, not taking into account the newer one that can replace the one just invented. In the real market situation, one must consider both competition and substitution phenomena between the old and new technologies. In assessing the benefit of new technology, it is necessary to take into account the fact that the technology will be substituted by newer technology sometime soon.

The main objective of this paper is to complement a shortcoming of the single generation diffusion model in assessing the value of technology. We apply a multigeneration diffusion model to CBS data used in Chapman's study [13]. Monte Carlo simulation is performed based on Taguchi design in order to evaluate the impact of uncertain factors on the value of specific technology invested. Organization of this paper is follows. Section 2, Chapman's study and related diffusion model for the economic assessment of new technology are summarized. Section 3 introduced extended model of our study. Section 4 describes Taguchi design for Monte Carlo simulation. Section 5 summarizes the results of our study. Finally, we describe the summary and further study.

2. CBA and diffusion model

Chapman [13] was concerned with the uncertainty involved in assessing the benefit of CBS technology, which is a multisystem configuration enable to communicate information and control functions simultaneously and seamlessly at multiple levels.

Cost invested on CBS is displayed in Table 1.

To evaluate the benefit to investment of CBS technology, the first thing needed was the forecasting of CBS demand. The Mansfield model was used for that purpose. The mathematical representation of the model is Eq. (1):

$$S_\eta(t) = \eta[1 + e^{\alpha-\beta t}]^{-1} \tag{1}$$

where $S_\eta(t)$: the proportion of potential users who have adopted the new technology by time t; η: the market saturation level (same as m subscribed in Bass model); α: location parameter; β: shape parameter.

Table 1
Investment cost of CBS technology (1991–2004)

Year	Investment cost by year (in millions of 1997 dollars)
1991	0.351
1992	0.307
1993	0.219
1994	0.206
1995	0.229
1996	0.307
1997	0.573
1998	1.445
1999	1.708
2000	2.125
2001	2.500
2002	2.125
2003	0.875
2004	0.375

The author considered uncertainties involved in introduction time, diffusion speed, saturation level, costs and savings of the technology and assumed baseline and extreme values of those parameters as described in Table 2.

One of the measures used for CBA by Chapman [13] was saving-to-investment ratio (SIR). That is Eq. (2):

$$\mathrm{SIR} = \frac{\sum_{t=t_b}^{T_b} A_t/(1+d)^t}{\sum_{t=-t_a}^{T_a} I_t/(1+d)^t} \tag{2}$$

where A_t: saving by time t: A_t=$(C_t - I_t) \times S_\eta(t)$, C_t: noninvestment cost by time t; I_t: investment cost by time t; [t_a,T_a]: investment period, $t_o > t_a$ base year of the study; [t_b,T_b]: introduction time in market, evaluation time (end of the study period); d: discount rate.

In addition to the Mansfield model, there have been many variations of diffusion models for assessing technology.

Bass [14] is one of the well-known and widely used technological forecasting model for the first-purchase demand. It is a model of the timing of adoption of an innovation and became the central to subsequent developments.

Norton and Bass [15] dealt with the dynamic sales behavior of successive generations of high-technology products. New technologies diffuse through a population of potential buyers over time. Therefore, diffusion theory models are related to this demand growth. Furthermore, successive generations of a technology compete with earlier ones, and that behavior is the subject of models of technological substitution. Building upon the Bass model, they developed a model, which encompassed both diffusion and substitution.

Mahajan et al. [16] suggested a diffusion modeling approach for assessing the impact of a new durable brand entry on market size and the sales of incumbent brands. The model is illustrated by applying it to the case involving Polaroid and Kodak in instant photography during the period 1976–1985.

Table 2
Parameter assumptions used Chapman [13]

	Probability distribution	Baseline	Minimum	Maximum
α	Uniform	6	5	7
β	Triangular	0.6	0.5	0.7
η	Triangular	0.175	0.0553	0.3082
Introduced time of CBS	Discrete	2003	2002	2005
Energy cost saving	Triangular	\$1.71	\$0.86	\$2.58
Maintenance cost saving	Triangular	\$1.60	\$0.81	\$3.23
Productivity cost saving	Triangular	\$4.20	\$0.00	\$8.39
Discount rate	Triangular	0.07	0.04	0.10

Speece and Maclachlan [17] used milk container data to show that Norton and Bass [24] may have applications in industries not usually associated with advanced technology, and in fitting individual submarkets and they added pricing and market growth factors to the diffusion model.

Kumar et al. [18] presented the results of a study that replicates and extends the findings of three previously published studies of cross-national diffusion. The purpose of their extension study was to evaluate the performance of a cross-sectional time-series model for the diffusion of innovations in several countries.

To test the hypothesis of dynamic price elasticity, Tam and Hui [19] extended existing growth models (e.g., Gompertz, Logistic and Exponential models) to include a price factor with different elasticity specifications. Nested specifications of three growth models were tested using spending data from 1955 to 1984 adjusted by a quality price index for computers.

3. Extended model

We extend Speece and Maclachlan [17] and Tam and Hui [19] models to incorporate a multigeneration substitution effect, as well as performance per price impact on the economic benefit of new technology.

Two-generation model can be written as Eq. (3):

$$\begin{aligned}
&S_1(t) = F_1(t)m_1 && \text{for } t \leq \tau_2 \\
&S_2(t) = 0 && \text{for } t \leq \tau_2 \\
&S_1(t) = F_1(t)m_1 - F_2(t-\tau_2)F_1(t)m_1 = F_1(t)m_1[1 - F_2(t-\tau_2)] && \text{for } t > \tau_2 \\
&S_2(t) = F_2(t-\tau_2)[m_2 + F_1(t)m_1] && \text{for } \tau_2
\end{aligned} \tag{3}$$

where $S_i(t)$: systems in use of ith generation at time t; m_i: ultimate numbers of adopters of ith generation; τ_2: introduction time of the second generation.

$$F_i(t) = \frac{1 - e^{-b_i t}}{1 + a_i e^{-b_i t}}$$

where $a_i = q_i/p_i$ and $b_i = p_i + q_i$; $F_i(t)$: fraction of the ultimate potential, which has adopted of ith generation by time t; p_i: innovation coefficient of ith generation; q_i: imitation coefficient of ith generation.

We suggest the performance per cost (P/C) function of each generation to be formed as Eq. (4):

$$G_i(t) = \left[\frac{P_i(t)/C_i(t)}{\overline{P(t)/C(t)}}\right]^{\rho} \tag{4}$$

where ρ: sensitivity coefficient of P/C; P/C: performance/cost(= cost saving/installation cost); $P_i(t)/C_i(t)$: P/C of ith generation at time t; $\overline{P(t)/C(t)}$: average P/C of all generations at time t.

We then multiply $G_i(t)$ by $F_i(t)$ and the resulting is Eq. (5):

$$F_i'(t) = G_i(t) \times F_i(t) \tag{5}$$

and substituting Eq. (5) with $F_i(t)$ in Eq. (3), $S_i(t)$ can be obtained as Eq. (6):

$$\begin{aligned}
&S_1(t) = F_1(t)m_1 && \text{for } t \leq \tau_2 \\
&S_2(t) = 0 && \text{for } t \leq \tau_2 \\
&S_1(t) = F_1'(t)m_1 - F_2'(t-\tau_2)F_1'(t)m_1 = F_1'(t)m_1[1 - F_2'(t-\tau_2)] && \text{for } t > \tau_2 \\
&S_2(t) = F_2'(t-\tau_2)[m_2 + F_1'(t)m_1] && \text{for } t > \tau_2
\end{aligned} \tag{6}$$

To find which conditions of the second generation affect economic value of the first generation CBS technology, we assume that investment cost and savings of the first generation is known while the diffusion process of both first and second generation is uncertain. So, we simulate uncertain situation in order to find influential factors on CBA.

4. Simulation

In simulating Eq. (6), we consider p_1, q_1, p_2, q_2, M_2, P/C, ρ, discount rate and τ_2 as random while parameters such as M_1 and τ_1 including some known factors as constant as displayed in Table 3. Investment cost, cost saving and installation cost are based on Chapman [13].

For random parameters, we assume distributions as given in Table 4.

In applying the Mansfield model, Chapman [13] also employed simulation in order to take into account uncertainty involved in the diffusion parameters of the first generation CBS

Table 3
Assumptions on fixed parameters

	Baseline
M_1	167.356
τ_1	2003
(1) Energy cost savings	\$1.71
(2) Maintenance cost savings	\$1.60
(3) Productivity cost savings	\$4.20
Total savings (per unit)=(1)+(2)+(3)	\$7.51
Installation cost (first generation)	\$11
P_1/C_1 (first generation)	0.6827

* P/C: performance/price(= cost saving/installation cost).

Table 4
Assumptions on random parameters

Variable	Probability distribution	Mean	Variance
q_1	β(150, 100)	0.6	0.0009562
$q_2(-)$	β(130, 130)	0.5	0.0009579
$q_2(+)$	β(154, 66)	0.7	0.0009502
p_1	β(30, 10 000)	0.003	0.0000003
$p_2(-)$	β(14, 7000)	0.002	0.0000003
$p_2(+)$	β(56.225, 14 000)	0.004	0.0000003

		Mean(min, max)
$M_2(-)$	Triangular	66(46, 86)
$M_2(+)$	Triangular	90(70, 110)
$P/C(+)$	Triangular	0.9(0.6, 1.2)
$P/C(-)$	Triangular	0.5(0.2, 0.8)
$\rho(+)$	Triangular	1.2(0.9, 1.5)
$\rho(-)$	Triangular	0.8(0.5, 1.1)
$d(+)$	Triangular	0.1(0.08, 0.12)
$d(-)$	Triangular	0.04(0.02, 0.06)
$\tau_2(+)$	Discrete	2010
$\tau_2(-)$	Discrete	2006

d: discount rate.

technology using triangular distributions. For instance, center values used for some parameters are $\eta(=0.172)$, $\alpha(=6)$ and $\beta(=0.6)$. In applying Eq. (6), we utilize these values to find corresponding parameters for the first generation model in Eq. (6). In Mansfield model, α is related to the initial share of the new technology, β is the growth rate of the share and η is the maximum market potential. So, they can be related to p_0, q_0 and M_0 in Bass model, But, unlike p_0, α itself is not the initial share. So, we equate p_0 with $\eta[1+e^{\alpha}]^{-1}$ for given α and η. That is $p_0(=0.003)$, $q_0(=0.6)$ and $M_0(=0.172)$. We utilize these values as the mean values of p_1 and q_1, which are assumed to follow β distribution. For the second generation, p_2 and q_2 are also assumed to follow independent β distribution but their mean values vary from p_0 and q_0. Hyper parameters for the distributions of other random factors are also set based on the first generation information.

Maximum market potential M_1 is obtained as proportion, which is estimated by total available installation area size (973 million square meters) according to the report of Chapman [13]: $M_1=M_0\times 973$, while the basis of the marginal increase due to the appearance of the second generation, M_2, may be 8% of the available installation area size (973 million square meters). That is the mean of $M_2=0.08\times 973$.

In order to define the performance per cost in Eq. (4), we consider the cost saving due to CBS technology as performance while the installation cost as cost. We fix the performance per cost for the first generation (P_1/C_1) as constant, while assume it random for the second generation ($P_2/C_2=P/C$). In addition, we consider two levels of hyper-parameters for random sensitivity coefficient, discount rate and market entry time for the second generation.

Table 5
Taguchi design matrix

	P_2	Q_2	M_2	τ_2	P/C	ρ
LEVEL(+)	0.004	0.7	65	2010	0.9	1.2
LEVEL(−)	0.002	0.5	90	2006	0.5	0.8
	X1	X2	X3	X4	X5	X6
1	–	−1	−1	−1	−1	−1
2		−1	−1	−1	1	−1
3	–	1	−1	−1	1	1
4		1	−1	−1	−1	1
5	–	−1	1	−1	1	1
6		−1	1	−1	−1	1
7	–	1	1	−1	−1	−1
8		1	1	−1	1	−1
9	–	−1	−1	1	−1	1
10		−1	−1	1	1	1
11	–	1	−1	1	1	−1
12		1	−1	1	−1	−1
13	–	−1	1	1	1	−1
14		−1	1	1	−1	−1
15	–	1	1	1	−1	1
16		1	1	1	1	1

Note that we used two different values of time horizon for T (5 and 10 years) in order to see the effect of different time horizon on CBA of CBS.

In sum, we have a total of seven factors to be considered in our experimentation. Among them, discount rate is uncontrollable and we use Taguchi design setting remaining six factors in inner array and discount rate in outer array. Orthogonal array used for the inner array is

Table 6
ANOVA for SN(SIR_5)

	DF	SS	MS	P value
P_2	1	5.5872	5.5872	0.5783
Q_2	1	0.1570	0.1570	0.9257
M_2	1	68.9333	68.9333	0.0510
τ_2	1	125.7216	125.7216	0.0084
P/C	1	46.8236	46.8236	0.1077
ρ	1	0.0898	0.0898	0.9438
$P_2 \times Q_2$	1	0.0232	0.0232	0.9714
$P_2 \times M_2$	1	0.0006	0.0006	0.9952
$P_2 \times \tau_2$	1	5.5872	5.5872	0.5783
$P_2 \times P/C$	1	0.0898	0.0898	0.9438
$P_2 \times \rho$	1	46.8236	46.8236	0.1077
$Q_2 \times \tau_2$	1	0.1570	0.1570	0.9257
$Q_2 \times \rho$	1	68.9333	68.9333	0.0510
$P_2 \times Q_2 \times \tau_2$	1	0.0232	0.0232	0.9714
$P_2 \times Q_2 \times \rho$	1	0.0006	0.0006	0.9952

Table 7
Duncan test for SN(SIR_5)

Duncan grouping	Mean	τ_2
A	68.3896	2006
B	67.8289	2010

given in Table 5 by employing 2^{6-2} fraction. For experimentation, each treatment is replicated 100 times based on Monte Carlo simulation. We measure SIR defined in Eq. (2) for each replication and calculate the signal to noise ratio (SN) for larger the better case at Eq. (7):

$$\mathrm{SN} = -10\log\left[\frac{1}{100}\sum_{j=1}^{100}\left(\frac{1}{2}\sum_{i=1}^{2}\frac{1}{y_{ij}^2}\right)\right] \tag{7}$$

where y_{1j} = SIR of jth simulation at + level of discount rate; y_{2j} = SIR of jth simulation at $-$ level of discount rate.

$$\mathrm{SIR}_T = \frac{\sum_{t=t0}^{T}\{(\text{saving per unit}) \times S(t) - (\text{installation cost per unit}) \times \Delta S(t)\}/(1+d)^{t}}{\sum_{t=t_a}^{t0} I_t/(1+d)^{t}}$$

Table 8
ANOVA for SN(SIR_{10})

	DF	SS	MS	P value
P_2	1	3.9803	3.9803	0.6725
Q_2	1	1731.8852	1731.8852	0.0001
M_2	1	147.1887	147.1887	0.0102
τ_2	1	122.5361	122.5361	0.0191
P/C	1	7645.2278	7645.2278	0.0001
ρ	1	6031.9383	6031.9383	0.0001
$P_2 \times Q_2$	1	0.5468	0.5468	0.8755
$P_2 \times M_2$	1	30.1177	30.1177	0.2450
$P_2 \times \tau_2$	1	0.7843	0.7843	0.8511
$P_2 \times P/C$	1	0.0797	0.0797	0.9523
$P_2 \times \rho$	1	869.5466	869.5466	0.0001
$Q_2 \times \tau_2$	1	1787.6346	1787.6346	0.0001
$Q_2 \times \rho$	1	149.9342	149.9342	0.0095
$P_2 \times Q_2 \times \tau_2$	1	1.2729	1.2729	0.8110
$P_2 \times Q_2 \times \rho$	1	30.6005	30.6005	0.2412

5. Results

Summarizing the simulation results, we conduct ANOVA for SN for $T=5$ and 10, separately: SN(SIR_5) and SN(SIR_{10}). In terms of SN(SIR_5), one main effect turns out to be significant as displayed in Table 6.

Table 9
Duncan test for SN(SIR_{10})

Duncan Grouping	Mean	Q_2
A	126.9043	0.5
B	124.8235	0.7

Duncan grouping	Mean	M_2
A	126.1672	90
B	125.5606	65

Duncan grouping	Mean	τ_2
A	126.1407	2010
B	125.5872	2006

Duncan grouping	Mean	P/C
A	128.0499	0.5
B	123.6780	0.9

Duncan grouping	Mean	ρ
A	127.8056	1.2
B	123.6780	0.8

Duncan grouping	Mean	$P_2 \times \rho$	
A	128.5926	0.0048	(+ +)
B	127.0185	0.0024	(− +)
C	124.6096	0.0016	(− −)
D	123.2350	0.0032	(+ −)

Duncan grouping	Mean	$Q_2 \times \tau_2$	
A	127.6846	1003	(− −)
B	126.1573	1407	(+ +)
B	126.1241	1005	(− +)
C	123.4898	1404.2	(+ −)

Duncan grouping	Mean	$Q_2 \times \rho$	
A	128.5398	0.6	(− +)
B	127.0713	0.84	(+ +)
C	125.2688	0.4	(− −)
D	122.5758	0.56	(+ −)

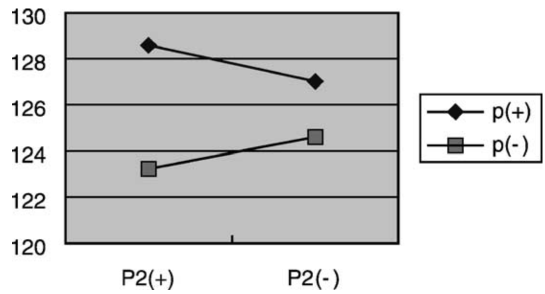

Fig. 1. Plot of $P_2 \times \rho$.

Duncan test result for τ_2 at significance level of 5% implies the following.

• Although the second generation appears in the market relatively early, it is even beneficial to the first generation by stimulating the already existing potential market of CBS (Table 7).

Significant factor interaction pattern changes when we do ANOVA for SN (SIR_{10}). Five main and three interaction effects turn out to be significant as displayed in Table 8.

Duncan test results for the main effects observed at significance level of 5% are shown in Table 9 and imply the following.

1. As the imitation coefficient of the second generation increases, the benefit of the first generation significantly decreases.
2. As the additional market potential due to the second generation increases, the benefit of the first generation technology significantly increases.
3. As the second generation appears in the market relatively late, the benefit of the first generation technology significantly increases.
4. As the relative performance of the second generation decreases, the benefit of the first generation technology significantly increases.
5. As the sensitivity coefficient of the performance per cost function increases, the benefit of the first generation technology significantly increases.

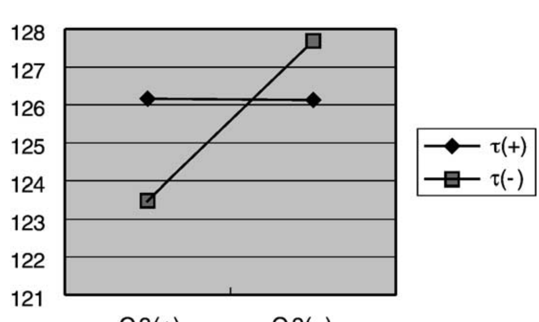

Fig. 2. Plot of $Q_2 \times \tau_2$.

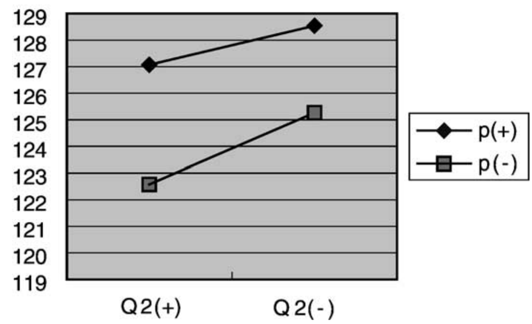

Fig. 3. Plot of $Q_2 \times \rho$.

In terms of the market entry time of the second generation, the results of both SN(SIR$_5$) and SN(SIR$_{10}$) are different. This phenomenon may represent temporal growth of the first generation at the early stage of the appearance of the second generation, which will eventually diminish as time goes on.

Interesting interaction effects are displayed in Figs. 1–3.

Duncan test result of two-way interaction effects at significance level of 5% implies the following:

$P_2 \times \rho$

1. When the second generation innovates fast, effect of cost elasticity on the first generation SIR is a lot larger than the case of slow innovation.
2. When the technology is relatively cost sensitive, SIR of the first generation is significantly larger when the second generation innovates fast.
3. In the relatively cost insensitive case, as the innovation coefficient of the second generation decreases, SIR of the first generation technology significantly increases.

$Q_2 \times \tau_2$

(1) When the second generation enters the market in a relatively short time after the first generation and its speed to imitation is slow, SIR of the first generation would significantly increase.

$Q_2 \times \rho$

(1) When the technology is relatively cost sensitive and the imitation speed of the second generation is low, SIR of the first generation is the highest.

6. Conclusion

In this paper, we proposed to use a multigeneration diffusion model for economic assessment of the new technology. Technology value evaluation has never been more important in the era of information age. Our approach enables decision-makers to implement several scenarios to perform CBA. As a result of employing the multigeneration model instead of the single generation diffusion, more conservative decision can be made in terms of the benefit of the new technology. This may prohibit potential overestimation in the early stage of planning of the new technology, which often occurs and gives heavy burden later. Using our approach, not only the overall benefit estimation but also influential factors on the economic value of technology can be identified for investment in the early age. To find which conditions of the second generation affect the economic value of the first generation technology, we used Monte Carlo simulation based on Taguchi design. With computational ability, careful consideration of additional external factors may be needed depending upon situations. Simulation model tuning is left as further study areas.

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