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PLANNING RENEWAL OF PRODUCT PLATFORMS FOR MANAGING TECHNOLOGY OBSOLESCENCE OF A PRODUCT FAMILY

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ABSTRACT
In the rapidly changing world, technologies quickly become obsolete and a product should be rapidly innovated. Under the platform-based product development strategy, innovation of a product is dedicated to the innovation of a platform. This study handles the problem of determining the optimal timing of innovating or renewing a product platform. While the frequent platform renewal harms profitability of the whole product family, a long lasting platform makes its derivative products obsolete, and unable to create new demands. In order to find the optimal platform life-time compromising such trade-off, a model for estimating the expected profit gained from a platform during a given life-time is developed. This model assumes that a newer product substitutes the demand for older products, and a platform is less likely to be able to adopt a newly developed technology as its life-time is getting longer. The cumulative sales of derivative products are estimated by a diffusion model, and various cases that a series of derivative products is introduced are examined by dynamic programming approach. When this model is applied to the IBM mainframe sales data, the optimal life-time is detected by varying the given life-times. The result shows that the optimal life-time is more sensitive to the speed of obsolescence than platform investment. For a long obsolescence duration, however, slowing down the obsolescence speed little contribute to increase the annual profit.

Keywords: Platform renewal, optimal platform life-time, technology obsolescence, diffusion model, dynamic programming

1. INTRODUCTION
In the rapidly changing world, technologies quickly become obsolete. A new technology enables a product to have more advanced functions and better performance. Due to such technological advancement, older products with an obsolete technology are substituted by newer products with a state-of-the-art technology. Especially for technology-driven products, the customers are highly susceptible to the functional performance and substitution to a newer product or technology is accelerated. In order for coping with the technology obsolescence, a company should continuously innovate its products by adopting state-of-the-art technologies.
Whereas continuous innovation adopting state-of-the-art technologies creates new markets, too frequent introduction of products damages profitability of individual products. Because the new product substitutes demand for the old product, the old product loses its potential sales which have not been realized until the new product is introduced. For this reason, a decision on when to introduce a new product compromising cost of the frequent development and benefit of the broadened market is crucial to the technology-driven companies. Determining the optimal entry timing of a new product has been studied by a couple of researchers [1-4].
This study handles the problem of determining innovation timing of product platforms. A product platform is a collection of common elements, particularly the underlying technology elements, implemented across a range of products, namely a product family [5]. Many companies reduce the cost and time of developing individual products by sharing a common platform. Since the products in a family are built upon a common platform, technologies implemented in a product are dedicated to the platform technologies. Even when a new technology is available to the company, a product implementing the new technology cannot be developed if it is incompatible with the platform technology. Therefore,

technology obsolescence also occurs at a family level, and it has to be overcome by renewing a product platform.
Then, when should be a platform renewed to the next generation technologies? The cost of frequent platform renewal is similar to the new-product introduction; cost of developing a platform, which usually takes much more cost than developing a derivative products, harms the profitability of the whole product family. On the other hand, a long lasting platform makes its derivative products obsolete, and unable to create new demands. Determining the optimal timing of platform renewal compromising this trade-off is one of the fundamental decisions on sustaining success in product development [6].
The objective of this study is finding the optimal life-time of a platform by developing a model for estimating the expected profit gained from a platform during a given life-time. This model assumes that derivative products based on a common platform are successively introduced, and a newer product substitutes the demand for older products. In order to reflect the obsolescence of platform technologies, the model assumes that a platform is less likely to be able to adopt a newly developed technology as its life-time is getting longer. Since we have to estimate the sales volume cumulated over time, the estimation model is basically based on the demand diffusion model proposed by Bass [7]. In addition, various cases that a series of derivative products is introduced according to the stochastic emergence of a new technology and its adoptability are examined by dynamic programming. The optimal life-time is detected by comparing annualized profits over the various life-times.

2. LITERATURE REVIEW

Platform-based product development strategy is a sound tool for providing various products at a low cost of differentiation. Previous literature introduces many of cases that a well defined platform drives a company to enormous success in the market by offering customized products both cheaply and quickly [5, 8-10]. A main issue of implementing platform-based development strategy has been how to plan ingredients of a product platform. Whereas there is variety of methods for the platform planning, most of them follow the basic framework proposed by Robertson and Ulrich [11]. In their framework, components that have little impact on differentiating variety of products and save much cost when they are commonized are included in the platform. Minimizing impact on differentiating features with commonized platform elements is also a basic principle in various methods for designing product platforms [12-16].
Whereas those platform studies focuses on how to design a single platform, it has been rarely studied how to plan upgrade and renewal of multiple generations of platforms. It is the nature of the market that a product is continuously innovated with a new technology or style, and older products become obsolete and finally vanished from the market. While a platform is usually utilized for multiple generations of products adopting new technology or market trends, it should also be upgraded or renewed when no more adoption is available due to the obsolescence platform technology itself. When to renew an old platform is a problem of optimizing tradeoff between efficiency and effectiveness of a platform strategy [6]. Although rapid renewal of a platform may guarantee its product family always state-of-the-art, high cost of platform development will ruin the efficiency of product development.
The purpose of this study is planning the optimal timing of renewal of a platform by estimating its revenue and cost for a given life-time.
As one of those kinds of methods, Gonzalez-Zugasti *et al.* [16] proposed a real-option based model for assessing value of a platform from which derivative products are successively developed. Whereas this model presents a basic framework for analyzing such a platform, life-time concerns of a platform, which are obsolescing technologies and depreciated development cost, are not involved. In a practical perspective, Meyer *et al.* [6] proposes efficiency and effectiveness indices of a platform for detecting appropriate timing of platform renewal. They insisted that a platform should be renewed when the efficiency or effectiveness metric drops below a reasonable range in its use. This renewal timing is detected only when it comes to the face, in the use of a platform. The model proposed in this study, however, can determine the optimal life-time of a platform even before introducing a platform, by predicting timely distributed development cost and revenue loss due to technology obsolescence.
The platform life-cycle or renewal issue is closely related to the problem of determining the entry timing of successively introduced products. At an individual product level, while a new product creates new markets and substitution demand for an old product, too early introduction may lose the sales of the old product. In order to find an optimal timing of introduction, a demand model forecasting dy-

namic growth of sales and substitution from an old product to a new product is required. Norton and Bass [3] developed such a model that shows cumulative sales of each product as a function of time adapting Bass's [7] demand diffusion model, which is a representative model of representing dynamic diffusion of new technologies or products in the market based on differential equations on change of sales. Wilson and Norton [4] derived optimal condition for introduction timing based on this model. They found that introducing a new product as soon as possible or never introducing a new product according to diffusion parameters, such as potential market size, gross margin, and speed of diffusion, is an optimal policy, which is called 'now or never' rule. Mahajan and Muller [2] also adapted the diffusion and substitution model of Norton and Bass [3] for finding an optimal policy of successive product introduction, and proposed 'now or at maturity' rule generalizing 'now or never' rule, which also indicates that a new product should be introduced immediately or after sales of an old product mature. They found this rule by deriving an optimal condition of the differential equations rather than optimizing the solution function of cumulative sales like Norton and Bass [3]. Whereas those models assume that a new technology becomes available at a deterministic timing, Krankel *et al.* [1] provided an optimal policy for the successive product introduction when a new technology stochastically emerges. They found that introducing a new product at the intermediate timing between 'now' and 'at maturity' can be optimal when obsolescence is stochastically incurred.

Those demand diffusion and substitution models are also adopted in this study in order for predicting total revenue during a platform life-time. Every derivative product has its own up-and-down sales revenue curve, and such individual curves are accumulated in a platform revenue curve. The obsolescence of technology prohibits to infinitely accumulating new product sales to an existing platform, since no more new product can be developed from an obsolete platform. The proposed model enables to predict the optimal timing of a platform by estimating sales curves of individual products and a cumulative sales curve of a platform.

3. MODEL

In this study, a model for estimating total profit gained from a product platform and its derivative products for a given platform life-time is developed. This model captures trade-off between high return-on-investment of a long lasting platform and lost demand caused by obsolete platform technologies. Whereas cumulative sales for derivative products continuously increase as time goes by, obsolete platform technologies limit to adopt state-of-the-art technologies which may create new markets.

Increased cumulative sales of individual derivative products are estimated by a model adapting Mahajan and Muller's demand diffusion and substitution model [2] based on Bass's model [7]. The expected profit from introducing a new derivative product is estimated by this model. When a new technology is available and can be adopted in the existing platform, introduction of a new product implementing that technology is determined by comparing expected profit of introduction and waiting the next technology. Emergence of a new technology and adoptability of it are stochastically determined, and the adoptability decays as the platform is getting older. In order to derive expected profit from the dynamic decision on introduction of new products, dynamic programming model is developed assuming that a company always makes an optimal decision.

3.1 Problem definition

This study assumes a product platform from which a series of derivative products are launched to timely differentiated markets. As time goes on, new technologies emerge and better products are introduced. While there are several strategies for leveraging a platform to synchronous market segments [17], timing of renewing a platform is not a concern in those leveraging strategies.

It is also assumed that a newer product totally cannibalizes demand for older products; newly created sales are solely for a new product, and old products are no more sold after a new product is launched. It should also be noted that the products are assumed to be durable products so that a product is only once purchased until it is upgraded to a better and later product.

Introduction of derivative products under those assumptions is illustrated in Figure 1. Platform-based derivative products are introduced in a sequence, and each product is marketed for different periods of time. Whenever an existing platform is fairly obsolete, a new platform is developed and derivative products based on the new platform are introduced in a series. The time periods between the last platform introduction to the next platform introduction is platform life-time. The model developed in this study finds an optimal platform renewal timing or optimal platform life-time by estimating profit gained from a platform and its derivative products.

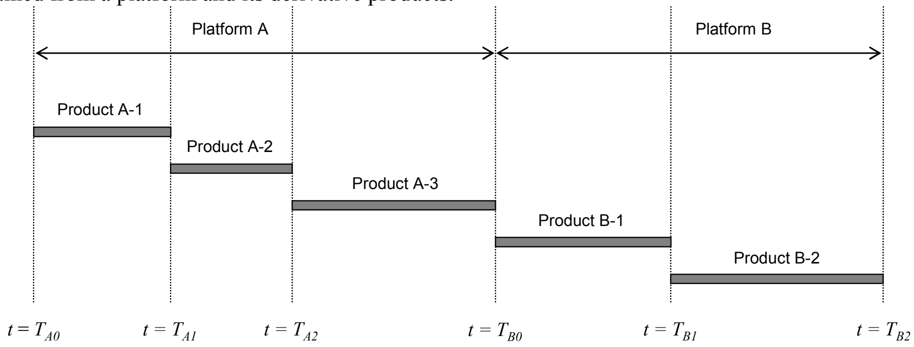


Figure 1. Product family introduction timeline

The profit of a product family and its platform is determined by benefit induced by sales of derivative products and cost of developing them. At each time period, a new technology is stochastically emerged, and a decision on whether to introduce a new product is made if it can be adopted by the existing platform. When a new product is introduced, sales of an old product gradually decrease and finally disappear in the market. The total cumulative sales of a product are determined by how long it has been existed in the market until a new product is introduced. In this paper, a diffusion model is adopted to estimate the sales of derivative products when they are sequentially introduced.

Since sale of a long-lasting product is finally saturated, a new product creating new demands should be introduced in order for gathering continuous revenue. As a platform is getting older, however, a new technology is prone to be incompatible with the obsolete platform technologies. In this case, a new product with state-of-the-art technologies cannot be introduced to the market, and new demand is also lost. Whenever a platform becomes obsolete, it should be renewed to an advanced platform which enables to develop a new generation of products.

In this study, emergence of a new technology and its adoptability to a platform is stochastically determined. Probability that a new technology is available at time t, $P_n(t_k)$, is assumed to follow an exponential distribution. $P_n(t)$ is $1-e^{-\lambda\Delta t}$ regardless of time t, where λ is a mean number of technologies emerged in a unit time, and Δt is length of a time period. Probability that a new technology emerged at time t_k is adoptable to a platform, $P_a(t_k)$, is assumed to decay following a sigmoid function $1-1/\left[1+e^{-12t_k/d+6}\right]$. Constant d indicates *duration of platform obsolescence* after which a platform cannot adopt a newly emerged technology. The adoptability function $P_a(t)$ have 0 probability after time d.

3.2 Sales diffusion model

As mentioned above, the profit gained from a product family is determined by sales of each derivative product. This study assumes that the increase of cumulative sales follows Bass's diffusion model [7]. The Bass diffusion model describes the diffusion of a technology or product consists of demand of innovators who adopt it without any word-of-mouth information and demand of imitators who mimics behavior of earlier adopters. The basic form of Bass's model is illustrated in equation (1).

$$g(T) = [a+bs(T)/N][N-s(T)] \qquad (1)$$

where $g(T)$ is number of consumers who adopt the technology at time T, $F(T)$ is a cumulative number of consumers who adopt the technology until time T, a is a coefficient of innovation, and b is a coefficient of imitation. This model can be interpreted that a ratio of potential consumers adopt the new technology at each time period, and b ratio of potential consumers imitates to adopt proportional to the earlier adopters.

Mahajan and Muller [2] extended the Bass's model so as to represent substitution of demand. Whereas there are several models involving substitution of demand, their model is suitable for a durable product that is purchased only once until it is upgraded to a later product. When there is only one product in the market, change of adopters is same as the basic Bass's model. In Figure 1, from $t=T_{A0}$ to T_{A1}, diffusion of product A-1 follows the basic pattern as follows:

$g_1(t) = [a+bx_1(t)/N_1][N_1-x_1(t)]$.

The total amount of cumulative sales is derived by summing up those partial changes of sales.

After T_{A1}, however, newly introduced products substitute the demand for the first product. Mahajan and Muller assume upgrade proportion α by which non-adopters purchase the new product and earlier adopters upgrade their products to the new generation. Under this assumption, diffusion of product A-1 and A-2 from T_{A1} to T_{A2} is made by following equations, respectively:

$$g_2(t) = \alpha[a_2 + (b_1x_1(t) + b_2x_2(t))/N_2][N_2 - s(t)] + \alpha[a_2' + b_2'x_2(t)/N_2]x_1(t)$$

$$g_1(t) = (1-\alpha)[a_2 + (b_1x_1(t) + b_2x_2(t))/N_2][N_2 - s(t)] - \alpha[a_2' + b_2'x_2(t)/N_2]x_1(t) .$$

This model assumes that innovation and imitation coefficients for the upgrading demand, which are represented by a' and b', is different from those of new demand. It should be noted that potential consumers of the later product include those of the older products. Thus, N_i is always smaller than N_j where $i<j$. It is straightforward to extend those equations to more generations of products. The cumulative sales of individual products can be obtained by those equations when introduction timing of each product is known as illustrated in Figure 1.

This study utilized the simplified Mahajan and Muller's diffusion model assuming the same innovation and imitation coefficients for every product. The simplified diffusion model enables to form a quasi-lattice model representing decision branches for successive introduction of products. How to build a quasi-lattice model and benefit of the quasi-lattice representation comparing to ordinary binomial tree representation is described in the next section.

Whereas the original model assumes different innovation, imitation, and upgrade coefficients for each product generation, the simplified model assumes the same innovation and imitation coefficients regardless of generations of a product. Also, the numbers of potential consumers for derivative products are set to the total potential consumers of the whole product family; every N_i is same with total potential consumers N. Therefore, the diffusion equations used in our model is defined as equations (2) and (3).

When there is only one derivative product in the market

$$g_1(t) = [a + bx_1(t)/N][N - x_1(t)] \quad (2)$$

When there are more than one products in the market

$$g_n(t) = [a + bs(t)/N][N - s(t)] + [a' + b'x_n(t)/N][\sum_{i=1}^{n-1} x_i(t)]$$
$$g_i(t) = -[a + bx_n(t)/N]x_i(t), i = 1,...,l-1 \quad (3)$$

The estimated parameter values of the simplified model are listed in Table 1. Those values are estimated by minimizing the squared deviation from the observed values using a MATLAB *fminsearch*() function.

Table 1. Estimated values of parameter of the simplified model

a	b	a'	b'	N

3.3 Stochastic derivative introduction model in a monopolistic market

How long a platform should be utilized for maximizing the overall profits is determined by comparing various platform life-times with respect to expected profits gathered from sale of derivative products, which can be estimated by the sales diffusion model described above. The expected profit varies, however, according to timing of introducing derivative products within the platform life-time as well as the life-time itself. Whereas delay of introduction may lose demand for a new product, frequent introduction takes more development cost and may lose opportunity for selling older products. For the fair comparison, various platform life-times should be compared by their maximum expected profits, which are obtained by optimally scheduled introduction of derivative products.

In this study, the optimal expected profit through a certain platform life-time is obtained by constructing a dynamic programming model for optimizing derivative introduction decisions. In this model, the whole platform life-time is fragmented by discrete time periods, and a decision on whether introducing a new product or waiting is repeatedly made at each time period, as illustrated in Figure 2. It should be noted that the market is assumed to be monopolistic; consumers have no other option than to choose the monopolist's product. Therefore, the market is dominated by the decision of the monopolist whether to introduce a new product or wait.

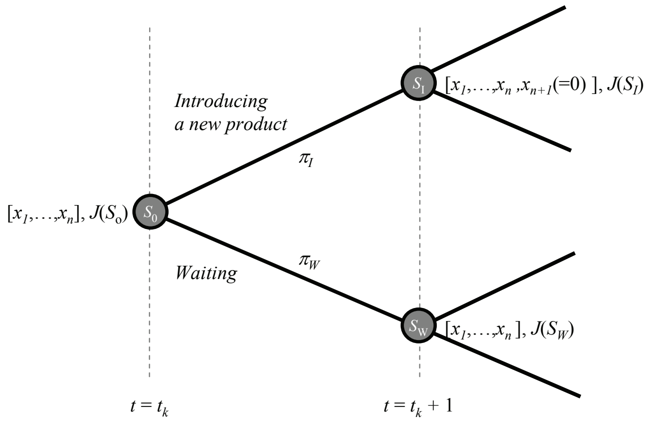


Figure 2. Decision branches on new-product introduction

Sales of derivative products at each time period are assumed to be determined by their cumulative sales until the last period, following the convention of ordinary sales diffusion models. In summary, the dynamic programming model is defined with states indicating cumulative sales of derivative products at each time period and binary branches to the next states indicating decisions on new product introduction and waiting.

At each time point, new product introduction is determined by comparing the profits from introduction and waiting. The current profit is computed by adding immediate profit, which is obtained in this period, to future profit, which is expected to be obtained from the next period. The future profit is, in other words, the current profit of the next state. The immediate profits induced by introduction and waiting, π_I and π_W, are assessed by computing revenue obtained by current sales of products based on the cumulative sales and cost for developing a new derivative. In Figure 2, the initial state S_0 goes to S_I or S_W according to whether a new product is introduced or not, respectively. If $J(S_I)$ and $J(S_W)$ are maximum profits that can be obtained from states S_I and S_W by making optimal decisions for each further time period, respectively, the optimal decision at current period S_0 is choosing an option that gives more value between $\pi_I+\delta J(S_I)$ and $\pi_W+\delta J(S_W)$, where δ is the one-period discounting rate. Therefore, the optimum profit of initial state S_0 is derived as equation (4).

$$J(S_0) = \max\{\pi_I + \delta J(S_I), \pi_W + \delta J(S_W)\} \quad (4)$$

This optimum value equation holds when adoptable new technology is always available to the company. In reality, however, a new technology is occasionally unavailable, and an old platform is prone to fail to adopt a newly developed technologies. In those cases, an option of introducing a new product is not available to a company, which has to wait regardless of its optimal decision. The deterministic dynamic programming model in equation (4) should be augmented to a stochastic model for incorporating this uncertainty. Then, the expected optimum value of state S_0 is defined as equation (5), where probabilities that a new technology is available and it is adoptable to a t_k periods old platform are $P_n(t_k)$ and $P_a(t_k)$, respectively.

$$EJ(S_0) = P_n(t_k)P_a(t_k)\max\{\pi_I + \delta EJ(S_I), \pi_W + \delta EJ(S_W)\} + [1 - P_n(t_k)P_a(t_k)][\pi_W + \delta EJ(S_W)] \quad (5)$$

The maximum expected profit from derivative products can be obtained by solving this stochastic dynamic program. The optimum value of each state is computed by applying the optimum value function from the last period to the initial period. The optimum value at an initial state is the maximum expected profit which can be obtained by optimally introduced derivative products.

3.3 Quasi-lattice relaxation of derivative introduction model

The objective of this study is estimating profit gained from a product platform. Since the profit from a platform depends on cumulative sales of derivative products which are determined by their introduction timing, platforms with different life time and obsolescing patterns should be fairly compared by assuming their derivative products are optimally introduced. To this end, we need a model to find optimal introduction of individual products. Sales of optimally introduced derivative products are estimated by the simplified Mahajan and Muller's diffusion model.

In this study, the optimal introduction schedule is obtained by a dynamic programming method. At each time period, decision on introducing a new product is made, and sales of derivative products in that period is determined by the introduction decision as illustrated in Figure 2. Since partial sales change in a period solely depends on cumulative sales until then, a state of the dynamic program is defined by cumulative sales of existing derivative products.

As an ordinary dynamic programming does, introduction decision at each time period is made by comparing profit of introduction with that of waiting. Immediate profits induced by introduction and waiting, π_I and π_W, are calculated from partial increase of sales in that period and cost of developing a new derivative product. The profit of introduction is summation of the immediate profit π_I and optimum value of the state of next period introduction $J(S_I)$. The optimum value $J(S_j)$ of any given state S_j is the maximum profit that can be gained from state S_j by optimally introducing afterward products. Likewise, the profit of waiting is summation of immediate profit π_W and optimum value of the state of next period introduction $J(S_W)$. The optimal decision on new-product introduction at state S_0 is choosing an option that gives larger profit than the other. Therefore, the optimum value of initial state S_0 is derived as follows:

$$J(S_9) = \max\{\pi_I + \delta J(S_I), \pi_W + \delta J(S_W)\}$$

where δ is a discounting factor.

This optimum value equation holds only when new technology is always available and adoptable to the existing platform. According to our assumption, however, a new technology stochastically emerges and its adoptability decays as a platform is getting older. If an adoptable new technology is not available at state S_0, an option of introducing a new product cannot be chosen. Where availability of an adoptable technology at time t_k is given with probability $P_a(t_k)$, the expected optimum value of state S_0 is defined as equation (4).

$$EJ(S_9) = P_a(t_k)\max\{\pi_I + \delta EJ(S_I), \pi_W + \delta EJ(S_W)\} + [1 - P_a(t_k)][\pi_W + \delta EJ(S_W)] \quad (4)$$

An expected optimum value of each state is assigned by this formula iteratively from the last period to the initial period. The expected profit gained from a platform is estimated by computing the expected optimum value of the initial state in the proposed dynamic program.

It is obvious that the dynamic program for estimating expected profit of a platform creates a binary tree since there are two options, introduction and waiting, for each state. Because the binary tree exponentially grows by factor of two, the dynamic programming technique cannot efficiently compute the expected profit as the number of time periods is getting bigger. This problem prohibits analyzing long horizon of the platform life-time.

In order for resolving this problem, this study introduces a way to reduce the binary tree to a quasi-lattice type tree. According to the Mahajan and Muller's model, partial sales of individual products, which determine gains at each period, depend on the numbers of cumulative consumers of the products, which are represented by a state vector. A closer look, however, reveals that new sales inducing actual gains only depend on the number of cumulative consumers of the whole product family and that of the latest product. In equation (3), new sales come only from the latest and the secondly latest products. Changes of consumers of the older products are the numbers of consumers who stop using the old products and upgrade to the newest product. Therefore, immediate profit induced by new sales at each period π is computed by the summation of positive terms of equation (3) and common profit margin m as follows:

$$\pi = m\left[(\alpha + 1 - \alpha)[a + bs(t)/N][N - s(t)] + \alpha[a' + b'x_n(t)/N][\sum_{i=1}^{n-1} x_i(t)]\right].$$

In this equation, $x_n(t)$ is $l(t)$ and summation of cumulative consumers of non-latest products $\Sigma x_i(t)$ is same as $s(t)$-$l(t)$. By replacing this term, we can derive equation (5) which computes immediate profit from the cumulative sales of individual products.

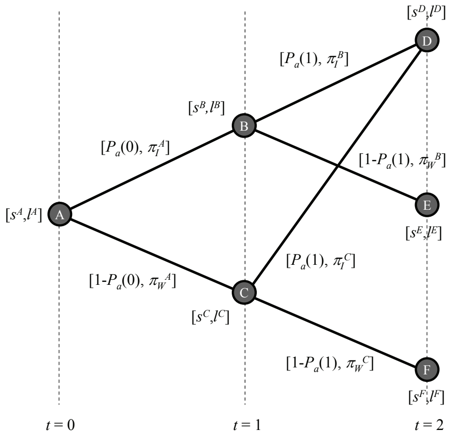
$$\pi = m\big[[a + bs(t)/N][N - s(t)] + \alpha[a' + b'l(t)/N][s(t) - l(t)]\big] \quad (5)$$

By equation (5), we can see that immediate profit at each period is a function of number of total consumers of a product family, which is $s(t)$, and that of consumers of the latest product, which is $l(t)$. In other words, immediate profit can be computed by $s(t)$ and $l(t)$ without requiring number of cumulative consumers of every product. Then, a state of the dynamic program which computes profit gained from a platform and its derivative products can be defined as a $[s(t), l(t)]$ pair.

Where a state is defined as [$s(t)$, $l(t)$], introduction of a new product leads to the same state at the next time period regardless of current states. Number of total cumulative consumers at next period $s(t+1)$ is increased by summation of all $g_i(t)$s from $s(t)$. As seen in the following equations, $s(t+1)$ is dependent on only $s(t)$.

$$s(t+1) = s(t) + [a+bs(t)/N][N-s(t)] \tag{6}$$

If we start from a single initial state, all states at the time period t have the same $s(t)$ regardless of its previous new-product introduction history.



$$s^B = s^A + (a + b\frac{s^A}{N})(N - s^A)$$
$$l^B = \alpha(a + b\frac{s^A}{N})(N - s^A) + \alpha a s^A$$

$$s^C = s^B$$
$$l^C = \alpha(a + b\frac{s^A}{N})(N - s^A) + \alpha(a + b\frac{l^A}{N})(s^A - l^A)$$

$$s^D = s^B + (a + b\frac{s^B}{N})(N - s^B)$$
$$l^D = \alpha(a + b\frac{s^B}{N})(N - s^B) + \alpha a s^B$$

$$s^E = s^D$$
$$l^E = \alpha(a + b\frac{s^B}{N})(N - s^B) + \alpha(a + b\frac{l^B}{N})(s^B - l^B)$$

$$s^F = s^D$$
$$l^F = \alpha(a + b\frac{s^F}{N})(N - s^F) + \alpha(a + b\frac{l^C}{N})(s^C - l^C)$$

Figure 3. Quasi-lattice representation of successive introduction decisions

If new-product introduction is waited, $l(t+1)$ simply becomes $l(t)+g_n(t)$ where $l(t)$ is $x_n(t)$. Since $g_n(t)$ is a function of $l(t)$, the next state is determined by the current state. Assuming that (n+1)th new product is introduced when there are n product at time t, $l(t)$ is $x_n(t)$ while $l(t+1)$ is $x_{n+1}(t+1)$. Because a new product has no cumulative sales when it has been introduced, $x_{n+1}(t+1)$ becomes partial sales of the newest product. Thus, $l(t)$ is computed by equation (7) when a new product is introduced.

$$x_{n+1}(t+1) = \alpha[a + bs(t)/N][N - s(t)] + \alpha[a' + b'x_{n+1}(t)/N][s(t) - x_{n+1}(t)] \text{ where } x_{n+1}(t) = 0$$
$$l(t+1) = \alpha[a + bs(t)/N][N - s(t)] + \alpha a's(t) \tag{7}$$

There is no $l(t)$ term in equation (7). It means that cumulative sales amount of the newly introduced product is determined independently from the last state. Therefore, every state at time t goes to the state [s(t+1), $l(t+1)(= \alpha[a + bs(t)/N][N - s(t)] + \alpha a's(t))$] when a new product is introduced.

Utilizing this property, we can construct a quasi-lattice representing successive decisions on new-product introduction as Figure 3. Whereas there are two states [s^B,l^B] and [s^C,l^C] at time t=1, they go to the same state [s^D,l^D] in case that a new product is introduced. If a new product is not introduced, the two states go to different states [s^E,l^E] and [s^F,l^F], respectively. In a quasi-lattice, the number of states at each time period increases by one instead of being multiplied by factor of two as a binary tree. The total number of states of a quasi-lattice spanning T time horizon is $(T+2)(T+1)/2$ which is a polynomial number.

The dynamic programming approach is applied to this quasi-lattice representation of successive product-introduction decisions. Summarizing the previous derivation and equations, the optimum value function of a quasi-lattice model is defined as equation (8).

$$\begin{aligned}
&EJ(\{s(t), l(t)\}) = P_a(t_k)\max\{\pi_I + \delta EJ(S_I), \pi_W + \delta EJ(S_W)\} + [1 - P_a(t_k)][\pi_W + \delta EJ(S_W)] \\
&s(t+1) = s(t) + [a + bs(t)/N][N - s(t)] \\
&S_I = \{s(t+1), \alpha[a + bs(t)/N][N - s(t)] + \alpha a's(t)\} \\
&S_W = \{s(t+1), l(t) + \alpha[a + bs(t)/N][N - s(t)] + \alpha[a' + b'l(t)/N][s(t) - l(t)]\} \\
&\pi_I = -k_v + m\big[[a + bs(t)/N][N - s(t)] + \alpha a's(t)\big] \\
&\pi_W = m\big[[a + bs(t)/N][N - s(t)] + \alpha[a' + b'l(t)/N][s(t) - l(t)]\big]
\end{aligned} \tag{8}$$

4. CASE STUDY: IBM MAINFRAME PLATFORM

4.1 Existence of optimal renewal timing of a platform

The optimal life-time of a platform is duration for which a company achieves maximum annual profit by marketing its derivative product. We can find such an optimal duration by enumerating various platform life-times, and assessing expected profit for each case using the quasi-lattice model based dynamic programming technique. As shown in Figure 4, annual profit for each planned platform life-time is estimated, and the optimal life-time can be determined by choosing a life-time indicating the highest annual profit.

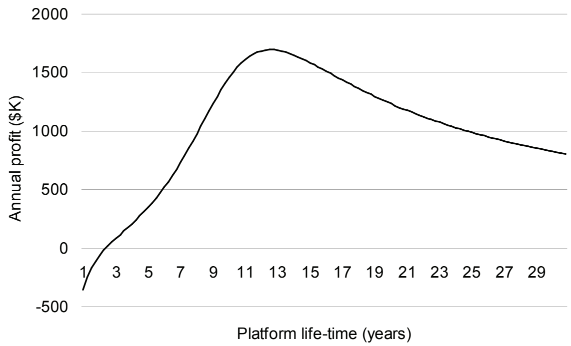


Figure 4. Annual profits for planned platform life-times (K_{pf} = $500K, d = 10 years)

Among parameters affecting the optimal platform life-time, investment cost in a platform development and speed of platform obsolescence are key parameters affecting the optimal life-time of a platform. Moreover, the two parameters are correlated each other. As a broader portion of a product is charged by a platform, platform development takes more cost. Whereas an expensive platform should be utilized for a long time in order to achieve high return-on-investment, a broad platform obsolesces faster than a narrow one since it has a bigger chance to encounter unadoptable innovations. Therefore, the optimal life-time is analyzed with respect to those two parameters.

Other factors, like rates of technological adoption involved in diffusion functions, investment in developing derivative products, and a discounting rate are mutually independent and monotonically affect the optimal life-time and profit of a platform. Where a product is faster adopted and developed with a lower cost, the optimal platform life-time shortens since considerable amount of profit overcoming investment in a platform can be obtained in a shorter time. A larger discounting rate lengthens the platform life-time since profit gained in a future is undervalued whereas immediate investment cost for a platform remains large.

4.2 Influence of obsolescence speed and platform investment

Figure 5 illustrates optimal life-time of a platform with respect to investment cost of platform development and duration of platform obsolescence. A platform can no longer adopt a new technology after the duration of platform obsolescence, as described in section 3.1. The diffusion parameters are derived from the IBM mainframe case. Gross margin of a unit product and investment cost of developing a derivative product are assigned to $1K and $100K, respectively. It is also assumed that internal interest rate of return is 20% per year.

Figure 5 shows contour plots for optimal platform life-times with respect to obsolescence duration and platform investment cost. It is found that the optimal platform life-time is longer than 12 years according to the optimal timing graph. Moreover, the optimal platform life-time remains to be around 12 to 13 years, specifically 12.5 years, until obsolescence duration reaches 13 years. It means that a platform is utilized for at least 12.5 years even though no more new product can be introduced. Since consumers have no other choice than to buy a monopolist's product, a single model is continuously sold in a market without being substituted by other products until the entire market purchases the product. Therefore, the monopolist has no incentive to introduce a new product before the market is saturated. After the market is saturated, however, the monopolist also has to renew its obsolete platform for introducing a new product creating new demands. We can expect different results for a competitive market, which is reserved for future research.

Another observation is that the optimal life-time is insensitive to platform development cost, contrary to the obsolescence duration. Since a platform lasts at least until the market is saturated, as mentioned, the platform investment cost takes relatively small portion than overall revenue which is over $20,000. In this situation, reducing annually distributed platform investment cost by utilizing it a year more brings even bigger loss of annualized sales revenue. Therefore, optimal platform life-time is dedicated to the time for maximizing annualized sales revenue rather than time for distributing platform investment.

As shown in Figure 6, a company can achieve amount of profit with infrequent renewal of platforms despite of rapid obsolescence of technologies. It is because the assumed monopoly guarantees that every consumer buys even an obsolete product since he/she has no other option. Even in this situation, slower obsolescence brings higher profit of platforms. The amount of increase, however, is small for short or long obsolescence durations. When obsolescence duration is shorter than 13 years, the optimal platform life-time is commonly 12 to 13 years, and difference of obsolescence duration does not induce large difference in overall profit. On the other hand, mitigation of profit increase in long obsolescence duration is originated in converging property of the annualizing function, which is $1/n$ in this study. Therefore, the amount of profit increase also converges to 0 accordingly.

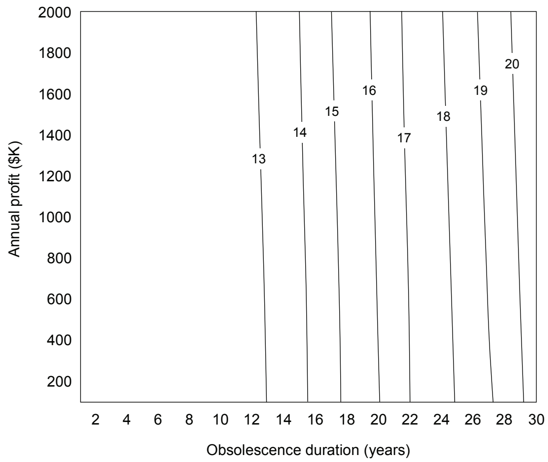


Figure 5. Optimal platform life-time

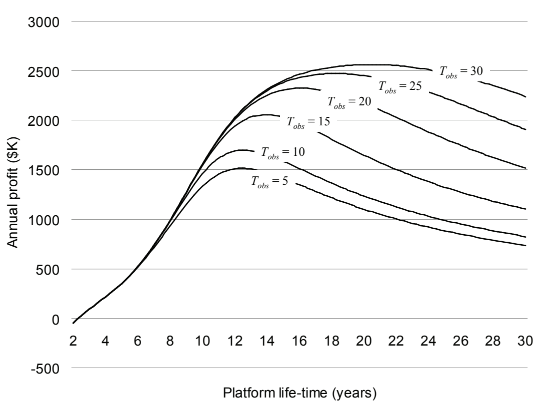


Figure 6. Optimal annual profit with respect to platform life-time (K_{pf} = $500K)

5. CONCLUSIONS AND FUTURE RESEARCH

How long a platform should be sustained is an important strategic decision of a company. Whereas a company wants to keep its platform as long as possible for achieving high return on platform investment, it may lose the market since a state-of-the-art product cannot be introduced from an obsolete old platform. The purpose of this study lies in supporting to make this strategic decision by finding the optimal renewal timing of a platform, which compromises trade-off between cost efficiency and technology obsolescence.

In principle, the optimal platform life-time maximizes the annual profit gathered from sales of platform-based products. The annual profit is obtained by subtracting the annualized cost from the annualized revenue. Whereas the cumulative revenue continuously increases as the life-time is lengthened, annualized revenue drops after no more products are sold in the market. The annualized cost naturally decreases as a platform is utilized for a longer duration. In order to find the optimal life-time, annualized revenue and cost have to be estimated with respect to various platform life-times.

This study proposes a method for estimating revenue and cost of a platform throughout a given life-time. The revenue gather from the sale of products are estimated by Muller and Mahajan's diffusion model which modifies Bass's original diffusion model for involving substitution of generational products. Costs for platform and derivative development are assumed to be raised when a platform and derivative product are introduced, respectively. Because the revenue and cost depends when and how many products are introduced, the maximum profit is obtained by a dynamic programming model which explores the optimal introduction schedule. The maximum profit for each life-time is compared to other life-times, and the one which presents the highest value is selected as the optimal life-time.

Based on the proposed model, the optimal platform life-time of IBM mainframe platform is estimated as a case study. The results show that there is an optimal life-time which brings biggest profit to a platform. Among other factors, the optimal life-time is mainly affected by obsolescence speed of platform technologies. It is also found that the increase of optimal profit according to the slowed obsolescence is mitigated as the obsolescence duration is getting longer. It means that efforts for slowing down the obsolescence speed are more beneficial for moderate obsolescence durations rather than originally long ones.

Whereas the platform investment cost also determines profit of a platform, it is revealed that the optimal life-time is fairly insensitive to the platform investment. Since an even obsolete product is sold until the market is saturated, under the assumption of monopoly, the platform investment takes relatively little portion in overall profit. This result may be different for a competitive market, which is reserved for the future research.

In this study, a method for determining how long to use a platform for achieving both cost efficiency and market effectiveness is developed. Whereas several meaningful results on platform life-time have been revealed, those are derived under the assumption of a monopolistic market. In the future research, optimal platform life-time in a competitive market will be analyzed. Additionally, the value of other strategies, such as enhancing robustness of embedding flexibility, for managing technology obsolescence without rapidly renewing a platform, will be assessed in order to support choosing the most profitable strategy among them.

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