Production-Sales Policies for New Product Diffusion under Stochastic Supply

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***Abstract*—In this study, we highlight the importance of production and sales plans for new products and illustrate the need for explicitly modeling supply uncertainties when making such decisions. We consider the case of variability in the production yield and perform extensive simulation experiments to study its impact on the performance of myopic and build-up policies in terms of the expected profit and risk measures. Managerial implications concerning selection of the production and sales plan are also discussed. The results show that ignoring the production yield variation can result in potentially incorrect decisions on the product launch time. The results also show that the policy selected based on the expected profit does not necessarily minimize risk.**

***Keywords*–Innovation diffusion; Production uncertainty; Production planning; Inventory management; Monte Carlo simulation.**

I. Introduction

New products play an important role in today's competitive marketplace. More than 30% percent of overall sales and profit of companies, on average, come from their new products [1][2]. It has long been known that the demand of new products follows diffusion patterns similar to those observed in epidemiology and natural sciences [3]. Once a new product is introduced into the market, some individuals (*innovators*) decide to adopt the product independently of others' decision while the timing of the adoption decision of *imitators* is influenced by word of mouth and pressure for adoption from the social system. Under certain circumstances and in the presence of extensive word of mouth spreading from past sales, if the company starts selling as many units as possible without building an initial inventory (*myopic* policy) the demand for the new product grows rapidly and soon may exceed the firm's capacity resulting in lost sales. To avoid this problem, companies generally delay product launch in order to build sufficient inventory prior to starting sales (*build-up* policy).

Decision making regarding an appropriate production-sales policy requires a deep understanding of the underlying dynamics of diffusion processes and can be difficult even for companies with a lot of experience in successful new product launches. For instance, Sony Electronics Inc. lost $1.8B in its game division and eventually laid off 3% of its workforce due to incorrect over-anticipation of the demand for PlayStation®3 [4]. In another case, Motorola Inc. who manufactured Power Mac G4 chips for Apple Inc., was unable to keep up with the rapid growth of demand for the computer [5]. Bandai Co. faced a similar problem in 1996 when the demand for Tamagotchi™, the first virtual pet, rapidly grew beyond expectations and led to lost sales. The company lost even more money when the demand declined right after they expanded their capacity in 1998 resulting in a $123 million in after-tax losses [6].

These cases prove that an effective production-sales plan is crucial to successful new product introduction. Several studies have addressed supply-restricted diffusion and evaluated various production-sales policies. However, existing literature ignores an important characteristic of any manufacturing environment: production uncertainty. Production systems exhibit significant uncertainties due to machine breakdowns, stochastic processing/tool changeover/setup times, labor availability, and quality uncertainty. These factors directly affect the supply levels and thus can influence the time to market the new product. As an example, in 2001, Microsoft Co. had to postpone the launch of Xbox® in Japan until next year and in the US by a week since they failed to meet the targeted initial inventory [7][8]. In this example, due to production uncertainties, the company needed more time than was expected to fully build the necessary inventory before the product launch. Therefore, the current literature leaves an important question unanswered: *How does uncertainty in production yield affect the company's choice of the production and sales plan?*

This paper aims to answer the above question by investigating supply-constrained new product diffusion in the presence of production uncertainties. More specifically, using a Monte Carlo simulation model, we evaluate the performance of different production-sales policies with respect to three performance measures, namely the expected Net Present Value (NPV) of profit over the product's life cycle and the 25^{th} and 75^{th} percentiles of the NPV of profit as two measures of risk. Through extensive experimentation, we demonstrate that ignoring production uncertainties can lead to an incorrect decision on the *best* production and sales plan under certain circumstances. Furthermore, the results indicate that the cost of making such incorrect decision is expected to increase with higher levels of uncertainty in the production environment.

The remainder of the paper is organized as follows. Section II provides a literature review and highlights the main contributions of this work. Section III describes the Monte Carlo simulation model. Experimental design and results are provided in Sections IV and V, respectively. Finally, conclusions and future research considerations are discussed in Section VI.

II. Literature Review

There are two main related streams of studies in the marketing and manufacturing literature. Both areas have been studied extensively. In fact, early studies on production/inventory management or diffusion models go back to as early as the 1960's [9][10]. The marketing literature primarily focuses on developing diffusion models to enhance demand forecasting while ignoring capacity constraints and assuming unlimited supply [11]. The manufacturing literature, on the other hand, typically involves finding the optimal production plan where the demand is assumed to be either deterministic or stochastic but following a known distribution [12][13]. In the real world, however, production constraints exist and the demand process is not exogenous. Therefore, what these studies fail to capture is the fact that supply constraints affect sales and past sales in turn have an impact on the future demand.

More recently, several studies have addressed the above issue which can be divided into two main categories based on the primary analysis tool used: analytical models and simulation studies. In the context of analytical studies, an equation-based model is proposed by Kumar and Swaminathan [14] to account for supply-constrained diffusion. The proposed diffusion model is used to evaluate the performance of myopic and build-up policies (calculated through numerical experiments) against the optimal policy (obtained by solving a mathematical model). In another study and using a similar diffusion model, closed-form expressions are derived for the demand and sales under supply constraints [15]. These expressions are then used to find the optimal capacity and time to market the new product. Myopic and build-up policies have also been studied in the presence of negative word of mouth from dissatisfied adopters [16]. A few studies also develop mixed-integer optimization models to find the optimal production and sales plan [17] and the optimal configuration of the supply chain for new products [18][19]. The primary performance measure used in all of the analytical studies presented here is the expected discounted profit over the life cycle of the new product. Moreover, none of these studies consider production/supply uncertainties.

The results of a recent survey on the application of Agent-Based Modeling and Simulation (ABMS) by Negahban and Yilmaz [11] indicate that only a few simulation studies have addressed supply-constrained diffusion processes. In [20], an ABMS is used to evaluate the performance of myopic and build-up policies with respect to the NPV of profit and lost sales under a fixed deterministic production level. In another ABMS study, Negahban et al. [21] develop a model where the company adjusts its production level based on forecasts of future demand and a production management strategy. In other words, adjustable production level is used as a substitute for building initial inventory. They evaluate the performance of different production management strategies with respect to the NPV of profit and lost sales under different planning horizons, social network structures, coefficients of innovation and imitation, and discount rates. Although the production level is not fixed, variation in production yield is not considered. Finally, a simulation framework is proposed by Negahban [22] for the newsvendor problem where the demand distribution is first predicted by ABMS while Monte Carlo simulation is used to select the optimal order quantity. The expected profit is the only performance measure while the underlying assumption is that the order will be available in full by the product launch (i.e., no variation in the supplier's production processes).

Our literature review reveals two major gaps in the existing body of knowledge. First, the impact of production uncertainties is not studied. Secondly, existing studies mainly focus only on the *expected* profit to select the best production-sales policy while the risk (which is generally an important factor for managers when making any financial investment) is not considered in the decision making process. The current paper contributes to the literature in three significant ways: (1) to the best of our knowledge, this is the first study that introduces the important notion of production uncertainty into the field of new product diffusion; (2) it uses percentiles to characterize the risk associated with different production-sales policies and shows that the policy with the highest expected profit is not necessarily the best choice under risk considerations; and, (3) it shows that the optimal production and sales plan can change based on the level of uncertainty in the production process.

III. Monte Carlo Simulation Model

A. Conceptual Model: Supply-Restricted Diffusion

The Bass model [10] is perhaps the most fundamental and widely used analytical diffusion model in the literature with the majority of other models being rooted in this model [23]. According to the Bass model, the demand of a new durable product at time period t, $d(t)$, is a function of the coefficient of innovation, p, coefficient of imitation, q, market size, m, and the cumulative number of adopters up to time t, $D(t)$, as follows: $d(t) = p(m - D(t)) + (q/m)D(t)(m - D(t))$. The Bass model was originally developed for diffusion of a product *class* (supposedly produced by many different firms) making supply constraints less relevant. However, here, we consider the case where the new product is produced and marketed by a single company. Therefore, it is possible that due to supply shortage, some adopters will not be able to purchase the product. As a result, the cumulative sales up to time t, $S(t)$, can be different from the cumulative demand, $D(t)$. Assuming that only those customers who have actually made the purchase will spread word of mouth about the product, supply shortage can influence word of mouth and demand growth rate.

Based on the above, we need a model that can capture the effect of supply constraints on the demand dynamics. In this paper, we use a modified Bass model proposed independently in [14] and [15]. The model can be expressed as follows: $d(t) = p(m - D(t)) + (q/m)S(t)(m - D(t))$. Thus, for a market with size m and at any given time t, a proportion of p of the remaining potential adopters (*innovators*) will adopt the product independently of the word of mouth influence. On the other hand, from the remaining potential adopters, the number of *imitators* that will adopt the product is proportional to the cumulative sales up to time t, $S(t)$, representing the effect of word of mouth. It is worth noting that the model is valid regardless of whether unmet demand $D(t) - S(t)$ is lost or backlogged for later fulfillment [14]. The model is also valid for the case of unlimited supply which essentially results in $S(t)$ being equal to $D(t)$ for all t. Therefore, the model is able to capture the impact of past sales on future demand. We will use this model to calculate the demand of the new product in the proposed Monte Carlo simulation model discussed below.

B. Monte Carlo Simulation Algorithm

In this model, there is a single company with a fixed average production level of L that markets the new product. In order to capture the impact of production yield uncertainty, we assume that the production yield varies around the average production level. The magnitude of this variation is determined by the percentage of variation in production yield, v. The actual production yield at each time step t, $y(t)$, is randomly sampled from the interval $[L(1 - v), L(1 + v))]$ based on a uniform distribution. Given $I(t-1)$ as the inventory carried over from

TABLE I. PARAMETER CHOICES FOR SIMULATION EXPERIMENTS

Parameter	Value/Range
Population-related parameters	
Coefficient of innovation, p	0.01, 0.03, 0.05
Coefficient of imitation, q	0.2, 0.4, 0.6
Market size, m	3000
Backlogging percentage, β	0, 0.5, 0.8, 1
Production-related parameters	
Average production level, L	100
Variation in production yield, v	0%, 5%, 10%, 15%
Unit production cost, c	1.0
Unit inventory/holding cost, h	0.001, 0.005, 0.01
Per customer waiting cost, w	0.001, 0.005, 0.01
Unit selling price, π	1.1, 1.2, 1.3
Discount rate, r	0, 0.003, 0.005, 0.01
Parameter related to the production-sales policy	
Number of inventory build-up periods, $T_{Build-up}$	0 – 25

the previous period, the total amount of supply at each time step will be $y(t)+I(t-1)$. The modified Bass model is used to calculate the *new* demand of the product at each time period, $d(t)$. Given there is backlogged demand waiting to be fulfilled from the previous period, $B(t-1)$, the *total* demand for the current time step will be $d(t)+B(t-1)$. Thus, assuming the company has already started selling the product, the instantaneous sales at t, $s(t)$, will be the minimum of supply and total demand, i.e., $min(y(t)+I(t-1), d(t)+B(t-1))$; otherwise, if the sales has not started yet (during periods of build-up), $s(t)$ will be zero. We assume that β percent of customers with unmet demand will wait to purchase the product later. At the end of each time period, the profit is calculated by subtracting the production cost, inventory cost, and cost of waiting customers from the revenue. At the end of the run (once the potential market m is almost entirely exhausted), the net present value of the profit over the diffusion time is calculated based on the given discount rate. The logic of the Monte Carlo model can be summarized in Figure 1.

IV. EXPERIMENTAL DESIGN

The experimental design is summarized in Table I. In order to select reasonable parameter choices and provide a common ground for comparison, the values/ranges are adopted from previous studies in the field [14][21]. It is worth noting that under each parameter configuration, we evaluate all integers between 0 and 25 for the number of build-up periods (with zero representing the myopic policy) and choose the best alternative as the best policy. Therefore, a total of 404,352 scenarios are studied. The simulation model is developed in MATLAB® and simulation experiments are run on a standard Dell™ desktop with a 3.00GHz quad-core CPU and 8GB of RAM.

V. ANALYSIS OF SIMULATION RESULTS

Once the Monte Carlo simulation model is developed and verified, it is used to evaluate the performance of myopic and build-up production-sales policies with respect to three metrics, namely the expected net present value of profit and the 25th and 75th percentiles of the NPV of profit as measures of risk [24]. The best production and sales plan is then the one that has the highest estimated value of the metric under consideration. In this section, we present the results of our extensive simulation experiments and outline the important findings.

```
% Model parameters
% Population-related parameters
Coefficient of innovation, p
Coefficient of imitation, q
Market size, m
Backlogging percentage, β

% Production-related parameters
Average production level, L
Percentage of variation in production yield, v
Unit production cost, c
Unit inventory/holding cost, h
Per customer waiting cost, w
Unit selling price, π
Discount rate, r

% Parameter related to the production-sales policy
Number of inventory build-up periods, T_{Build-up}

% Pseudo-code for supply-constrained diffusion under production yield uncertainty
% Initialize model variables at time 0
Set initial time step, t = 0
Set initial cumulative demand, D(0) = 0
Set initial cumulative sales, S(0) = 0
Set initial backlogged demand, B(0) = 0
Set initial inventory level, I(0) = 0

% Iterate by incrementing time step until the market potential is exhausted
While there is demand for the new product
    t = t + 1
    Sample production yield, y(t) ← U(L(1 − v), L(1 + v))
    Demand, d(t) = p(m − D(t − 1)) + (q/m)S(t − 1)(m − D(t − 1))
    Update cumulative demand, D(t) = D(t − 1) + d(t)
    % Calculate sales (do not sell if still in build-up period)
    If t ≤ T_{Build-up}
        s(t) = 0
    Else
        s(t) = min(y(t) + I(t − 1), d(t) + B(t − 1))
    Endif
    Update cumulative sales, S(t) = S(t − 1) + s(t)
    Remaining inventory, I(t) = I(t − 1) + y(t) − s(t)
    Backlogged demand, B(t) = max(0, d(t) + B(t − 1) − s(t)) ∗ β

    % Calulcate revenue, total cost, and profit
    Revenue, R(t) = π ∗ s(t)
    Total cost, C(t) = c ∗ y(t) + h ∗ I(t) + w ∗ B(t)
    Profit, P(t) = R(t) − C(t)
End While

% Compute net present value (NPV) of profit
NPV = 0
For i = 1 to t
    NPV = NPV + P(t) ∗ (1 + r)^{1−t}
End
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Figure 1. Pseudo-code of the Monte Carlo simulation model.

A. Expected Profit vs. Risk

While previous studies only use the expected profit to select the best policy, with the presence of production uncertainty, we can also evaluate the associated risk. The research question under investigation then becomes whether the best policy changes based on risk. In order to answer this question, for

TABLE II. NUMBER OF CASES WHERE THE BEST POLICY IS DIFFERENT BASED ON RISK MEASURES

Risk Measure	Production Variation (v)		
	5%	10%	15%
25th percentile of profit	28	73	109
75th percentile of profit	29	51	90
Total	57	124	199

all parameter configurations, we first find the best policy under each of the above three criteria. We then identify the scenarios where the best number of build-up periods based on the expected NPV of profit is different from the best policy based on the 25th or 75th percentiles. Statistical hypothesis tests are then performed to detect statistical difference between the corresponding percentiles of the resulting two candidate policies. If a statistical difference exists, then we can conclude that the risk associated with the policy selected based on the percentile under consideration is actually more desirable than the policy with the best NPV of profit.

The number of scenarios (out of 3,888 parameter configurations) where a significant statistical difference was detected is provided in Table II. The results show that the policy with the highest NPV of profit does not necessarily have the minimum risk. In other words, the decision on the production-sales plan can change if the primary criterion is risk rather than the expected profit. This is an important finding since existing studies select the best policy only based on the expected profit while the risk has been ignored. High levels of production uncertainty not only increase variability in production cost, but also affect supply which in turn has an impact on future demand. As a result, a higher uncertainty level is expected to increase variability of NPV of profit and have a greater impact on the risk associated with it making consideration of risk measures even more important.

We also investigate the impact of production variation under different diffusion parameters namely coefficients of innovation (p) and imitation (q). Given p, q, and v, there are 432 scenarios. Figure 2 shows the number of cases where the best number of build-up periods chosen based on risk is different (statistically) from the one based on the average NPV. The figure shows that the impact of production uncertainty varies based on p and q. We believe this is mainly due the fact that different combinations of p and q impact the dynamics of the problem in a different way (essentially, p and q affect initial demand and its growth rate). For instance, when both p and q are small, the initial demand levels are low and the demand grows slowly. In such cases and under the best policy, the demand rarely exceeds supply resulting in almost no backlogged or lost demand (supply abundance). On the other hand, when both p and q are large, the initial demand level and its growth rate are both high resulting in high levels of backlogged or lost sales (supply scarcity) which in turn affect the future sales and demand. Therefore, for other combinations of p and q, we expect to see different degrees of these two effects and thus a different impact by production yield variation on the best number of build-up periods as shown in the figure.

It is worth noting that since standard hypothesis testing procedures are not readily available for comparing ordinal values of two populations, nonparametric tests will be necessary when comparing percentiles [25]. In this paper, for all of the statistical tests for comparing the percentiles, we use a nonparametric double bootstrap method which is also based on Monte Carlo simulation sampling; however, since statistical techniques are out of the scope of this paper and for the sake of conciseness, the details are not provided here. The reader is referred to Spiegelman and Gates [26] for more information.

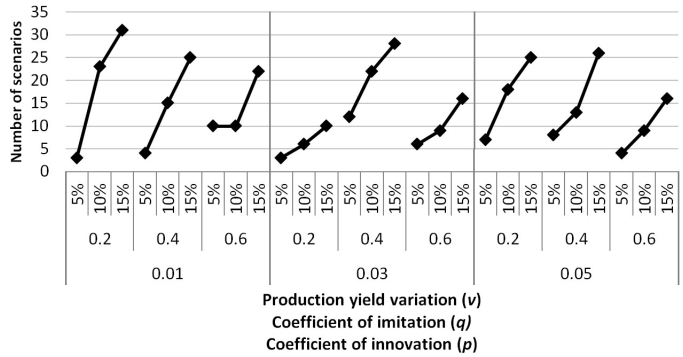

Figure 2. Number of cases where the best policy is different based on risk.

B. Deterministic vs. Stochastic Production Yield

The results presented in this section assess the impact of supply uncertainty on the best production-sales policy. Although the case of Xbox® in 2001 (discussed earlier in the paper) shows that such uncertainties matter, no theoretical work has been done in this area. The research question to be answered is whether the best policy can change if variation in production yield is explicitly considered. In order to answer this question, for each performance measure, we first identify the scenarios where the best number of build-up periods for the deterministic case ($v = 0$) is different from the best policy with production yield variation taken into account ($v > 0$). Statistical tests are then performed to test the significance of these differences. For the resulting two candidate policies, Welch's t-test is used to test the difference in average NPV of profit while a double bootstrap method is used for comparing the 25th and 75th percentiles of the profit.

The number of cases (out of 3,888 parameter configurations) where production yield variation has actually changed the best number of build-up periods is provided in Table III. For instance, when the 75th percentile of the profit is used as the primary performance measure, a 15% variation in the production yield results the optimal decision to be different from the deterministic case in 179 parameter configurations. The results are inline with our expectation from empirical findings that supply uncertainties affect the number of build-up periods needed to build the required initial inventory. Therefore, we have shown that variation in production yield is an important factor that needs to be explicitly modeled when evaluating production-sales policies. The results also suggest that, in general, higher levels of production variation is expected to increase the likelihood of making an incorrect decision on the best number of build-up periods if ignored.

Given p, q, and v, Figure 3 shows the number of scenarios (out of 432) where the best number of build-up periods is different (statistically) from the deterministic case for at least one of the three performance measures. As expected, for

TABLE III. NUMBER OF SIGNIFICANT STATISTICAL DIFFERENCES FROM THE DETERMINISTIC CASE

Performance Measure	Production Variation (v)		
	5%	10%	15%
Average NPV of profit	64	53	79
25th percentile of profit	83	88	101
75th percentile of profit	75	108	179
Total	222	249	359

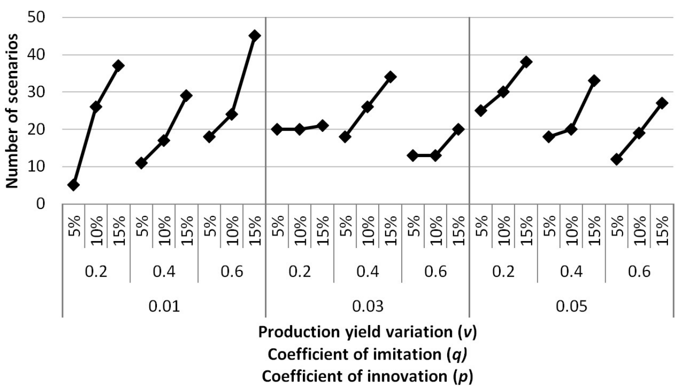

Figure 3. Number of statistical differences from the deterministic case.

all combinations of p and q, we see an increasing trend in the number of changes in the best production-sales plan. Furthermore, similar to the results of the previous section, due to the complex supply-sales-demand inter-dependencies and also the nonlinear effect of the coefficient of imitation, we expect the impact of production yield variation on the best policy to vary for different levels of p and q.

C. Practical Implications

We have shown that production uncertainties affect the best production-sales plan. Companies can easily overlook these uncertainties and thus make a potentially incorrect decision about the required level of initial inventory and time to market the product. In this section, we present three main aspects of our findings that can provide deeper insights for managers.

Change in the best number of build-up periods: The results show that in the presence of production uncertainties, the length of the build-up period can range from as much as 2 periods shorter to 3 periods longer than the deterministic case, illustrating a significant perspective difference from the case where production variation is ignored (Figure 4). However, in most cases, this difference is only one period. In the presence of variation, if the company gets lucky (if they produce more than the average production level in several consecutive periods), it is possible that they can reach the targeted initial inventory faster enabling the company to market the product earlier. This will move the revenues closer to the present time and reduce inventory costs resulting in higher profits. Therefore, when using the average NPV or the 75th percentile of profit, in most cases, ignoring production uncertainties would yield to a policy where the length of the build-up period is one period longer. On the other hand, in order to guarantee that the initial inventory will be met by product launch, the company will generally need longer periods of build-up to reduce the loss of sales due to insufficient supply which is why

TABLE IV. MAXIMUM PERCENTAGE OF DIFFERENCE FROM THE DETERMINISTIC CASE ($v = 0$)

Risk Measure	Production Variation (v)		
	5%	10%	15%
Average NPV of profit	0.22	0.35	0.53
25th percentile of profit	0.30	0.54	0.94
75th percentile of profit	0.39	0.78	1.03

for the case of the 25th percentile, if production uncertainty is ignored, it is more likely that we incorrectly select a build-up period that is one period shorter than the actual best value.

Magnitude of statistical differences: The magnitude of difference from the deterministic case can be thought of as the expected cost of making an incorrect decision by ignoring production uncertainties. This cost is expected to increase with higher levels of variation which also matches the results presented in Table IV. Moreover, the results also indicate that the 75th percentile is more sensitive to these variations than the other two performance measures for all levels of v. Therefore, when the probability of making higher profits is the primary risk factor, considering the uncertainties in the production processes becomes even more important for companies.

Practical difference: The magnitude of difference discussed above is also important when considering the concept of *meaningful practical difference* (δ) defined as the minimum difference that is important to detect. Thus, a difference of less than δ between the performance of two policies is considered *practically* insignificant although a statistical difference is detected. For example, if a difference of d is detected between the performance of the best policies in the deterministic and stochastic cases, the effect of production variability is practically insignificant if $d < \delta$. The minimum practical difference can also be used to determine the number of replications. When comparing two different policies, a sufficiently large sample will suggest a statistical difference at any level of significance since it enables us to detect even minute differences between the two samples. Therefore, after running the model for an initial number of replications, we can stop if a difference of less than δ is detected suggesting that the two alternatives are not practically different. Using the same approach, the number of replications for our experiments was chosen to be 1,000 based on a set of pilot runs.

VI. CONCLUSION AND FUTURE WORK

Through comprehensive experimentation using Monte Carlo simulation, we investigate the effect of production uncertainty on the best production and sales plan for new products and show that the time to market can be affected by variations in production yield. We also compare production-sales policies with respect to measures of risk and show that the policy with the maximum expected profit does not necessarily minimize risk. Finally, we discuss theoretical and practical implications of the findings to provide deeper insights on supply-restricted diffusion for both researchers and practitioners.

Myopic and build-up plans are heuristic policies that may not necessarily lead to the *optimal* policy [14]. The impact of supply uncertainties on the optimal production-sales plan is currently under investigation by the authors. Moreover, the only type of uncertainty considered here is production yield

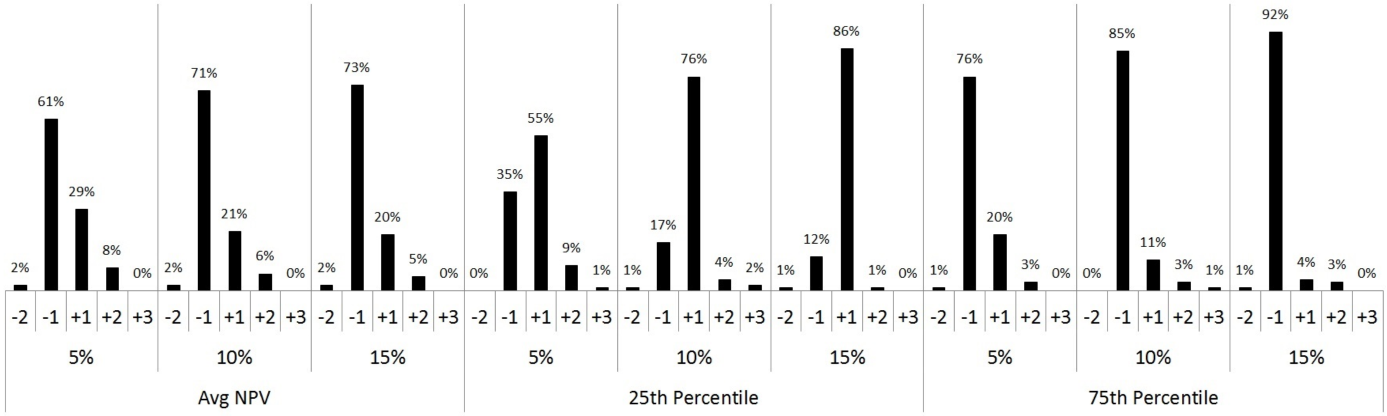

Figure 4. Distribution of the change in the best number of build-up periods from the deterministic case.

variation. Different sources of uncertainties exist in a supply chain making the study of the impact of other types of uncertainties on diffusion dynamics an interesting area for future research. Finally, studying the impact of other distributions for variations in production yield on the findings of this paper would be another interesting extension for future research.

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