Planning and managing manufacturing capacity when demand is subject to diffusion effects

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Abstract

When launching a new product, the manufacturing and marketing functions of a firm are required to jointly take critical decisions concerning the amount of manufacturing capacity to be acquired, and to elaborate policies for managing it over the product’s life cycle. The time-varying demand profile caused by new-product diffusion phenomena, together with learning effects, cause the emergence of critical trade-off decisions among the options of increasing production capacity, delaying launch, increasing backlog or accepting a significant amount of lost sales. In this paper these trade-offs are studied by developing a simple Mixed-Integer Linear Programming model and by experimenting upon it with realistic data representing different scenarios. Optimal policies arising from the experiments are then compared and discussed. © 2000 Elsevier Science B.V. All rights reserved.

Keywords: Manufacturing capacity planning; New-product launch; New-product diffusion

1. Introduction

Recent literature has often advocated the need of stronger interfunctional integration in manufacturing operations. Authors have generally emphasised interface issues arising between marketing and product development [1] and between product development and manufacturing [2]. A third interface, between marketing and production, has received scant attention in past literature and has only recently been examined with greater care [3–9]. Readers interested in the subject may also refer to the survey by Eliashberg and Steinberg [10].

In the field of production–marketing co-ordination, reference is generally made to a seminal paper by Shapiro [11]. The author proposed a framework identifying eight areas of necessary co-operation but potential conflict within the marketing–production interface. This paper focuses upon the two areas of capacity planning and new-product introduction. Shapiro [11], who viewed capacity planning and long-range sales forecasting as strategic issues, discussed the importance of accurate forecasts in making proper decisions regarding the size of investment in manufacturing capacity. Such decisions are critical, since investments made to develop excess capacity are difficult to recover, while insufficient capacity leads...
to foregoing sales and market share. Issues related to new-product introduction are seen by Shapiro [11] to be more tactical in nature. At launch time the novelty of the product may lead to high levels of demand but, simultaneously, the manufacturing facility has not accumulated enough experience with the product and the process to work at capacity. The learning phenomenon is therefore a crucial factor to take into account when managing new-product introduction. As suggested by Jaber and Bonney [12], the learning effect may force to backorder part of the initial demand at the time in which capacity is not sufficient. Other available tactical decisions are building inventory in advance, eventually by purposefully delaying launch, and accepting lost sales.

Both strategic and tactical problem areas are becoming extremely important in today’s competitive environment. Capital investment required to acquire advanced manufacturing technology is increasingly high, thus making accurate capacity planning a growing concern for manufacturing operations. Moreover, increased global competition makes it essential for a firm to fully exploit opportunities given by the market: the short- and long-term opportunity costs related to losing part of the available demand to competition may hinder the long-term welfare of the firm [13]. In addition, product life cycles have significantly shortened in recent years [14], while there is a growing uncertainty related to markets and technology. These factors ultimately force firms to narrow the horizon upon which strategic choices related to capacity are performed, so that these become “one shot” decisions leaving little room for later adjustments. Such competitive environment therefore urges firms to consolidate decisions related to manufacturing capacity planning and management over the product’s life cycle.

This integration of “strategic” and “tactical” decision levels makes this paper somewhat different from literature on capacity planning, which generally focuses upon optimal expansion policies with a steadily growing demand over medium-to-long time horizons [15,16]. Amit and Ilan [17] discuss capacity planning when demand follows a Mansfield-type, or epidemic, diffusion phenomenon. Epidemic diffusion is due to word-of-mouth effects within the market and does not consider the exogenous role of advertising upon adoption decisions. It leads to a cumulated demand that follows an S-curve, in which low demand occurs immediately after launch, followed by a period of growth and then by decline when the market reaches saturation. This paper may be seen as an extension of Amit and Ilan [17] in the direction of considering tactical issues and more complex diffusion phenomena. The approach of combining capacity planning with tactical decisions is also similar to that followed by Ulusoy and Yagzac [9] and Khmelnitsky and Kogan [18]. These authors however do not consider demand profiles influenced by diffusion effects, nor do they take learning phenomena and lost sales into account.

This paper also differs from literature on the management of style goods and perishable items [8]. Such problems are characterised by a very short selling season, so that most production must take place in advance, based upon a probabilistic forecast of demand. In this paper we deal with the diffusion of a new product, which generally occurs on a longer time scale than the life of a style or perishable good, so that production normally takes place during the selling period and not before. The main up-front decision to be taken in our paper is therefore how much manufacturing capacity to install, and not how much to produce.

This paper is structured as follows. In Section 2 the main factors and trade-offs to be taken into account are discussed, thus leading to the development of a Mixed-Integer Linear Programming (MILP) model. Section 3 describes experiments made upon this model with realistic data, which have given optimal policies for a number of possible scenarios. Managerial implications and conclusions are then drawn in Section 4.

2. Conceptualising and modelling the problem

Section 1 identified the scope of the paper as to the planning and management of manufacturing capacity over the product life cycle, where this section discusses the levers available for managerial decision making and trade-offs among them. Concerning the competitive scenario, it has been
decided for simplicity that the price has already been set, either by a previous decision by the firm or by the market. The price has also been assumed to be constant over the product life cycle, even if it would be straightforward to modify such assumption and to study the case of given dynamic pricing strategies, such as penetration pricing or price skimming. In addition, the market has been considered large enough, so that actions taken individually by the firm are unable to affect the overall diffusion phenomenon.

2.1. The side of marketing — diffusion effects

It is known that demand for new products does not maintain itself constant over the life cycle. Demand generally requires some time to build up and, after peaking, it decreases. When product life is short this surge in demand casts an important problem for the manufacturing firm, since production capacity must be decided once and for all, thus implying a trade-off between acquiring greater capacity; i.e. incurring higher investment costs, and losing part of the demand. This loss may be moderated, but only to some extent, by building up inventory before the peak occurs (eventually by deliberately delaying product launch), or by accepting backorders during the peak. These options have drawbacks, since carrying inventory comes at a cost, while delaying product launch leads to losing sales in the short run and may also reduce market share in the future [19]. Concerning backorders, these may be associated with a cost due to discounting or to the offering of complementary benefits. A high level of backorders may also discourage some customers, thus leading to additional lost sales. One may therefore distinguish between these latter “involuntary” lost sales and the “voluntary” ones that the firm accepts when it decides for an insufficient manufacturing capacity.

This paper discusses the case of durable products, in which sales coincide with new-product adoptions and the peak in demand is more significant because replacement sales are absent. The diffusion phenomenon has been represented following Bass’ model [20], which is an extension to the previously mentioned epidemic diffusion model. Alternative models, as reviewed by Mahajan et al. [21], may also be considered. The Bass model assumes that:

(i) the product is durable;
(ii) market potential is constant over the entire life cycle. In this paper it is assumed that the firm’s specific offering is such as to secure it a given share of this potential;
(iii) there is no relationship of substitutability or complementarity with other types of products, which could influence the diffusion process;
(iv) price and other marketing variables are given and constant in time;
(v) adoption decisions taken by individual customers at each instant are binary (i.e. do not adopt yet vs. buy one unit only);
(vi) there is no limitation in supply so that overall demand equals industry sales at all times. This implies that, if the firm is short in supply, this will not affect the aggregate diffusion process. The assumption holds if not all firms install an insufficient manufacturing capacity, or if entrance barriers are low enough, allowing new firms to enter the market.

The Bass model assumes that, at each moment in time, $t$, the potential market, $M$, is split among a number of customers who have already adopted, $N(t)$, and others who have not, $M - N(t)$. The rate of adoption, $n(t)$, is due to individuals either exhibiting innovative behaviour or responding to word-of-mouth. The formers are subject to external influence, such as advertising, so that at each time interval a constant quota $p$ of residual non-adopters adopt. The latter depend upon how many adopters are spreading the word, so that at each time interval their number is proportional to both the number of residual non-adopters and to the number of adopters, via a factor $q/M$. Bass’ model is formulated as follows:

$$n(t) = \frac{dN(t)}{dt} = p[M - N(t)] + \frac{q}{M}N(t)[M - N(t)].$$

(1)

Differential equation (1) yields the following expressions for the rate of adoptions, $n(t)$, and the
cumulative number of adoptions, $N(t)$:

$$n(t) = M \left[ \frac{(p + q)^2 e^{-\frac{(p + q)t}{(p + q)^2}}} {p + q e^{-\frac{(p + q)t}{(p + q)^2}}} \right] = M r(t),$$

(2)

$$N(t) = M \left[ \frac{1 - e^{-\frac{(p + q)t}{(q/p)e^{-\frac{(p + q)t}{(q/p)^2}}}}} {1 + (q/p)e^{-\frac{(p + q)t}{(q/p)^2}}} \right].$$

(3)

Parameters $q$ and $p$ principally depend upon product type [22], with the word-of-mouth effect prevailing in the case of expensive durables, and innovative behaviour prevailing with non-expensive ones (as well as with first-trials of consumables). The firm has some latitude in influencing these parameters, since $p$ depends upon advertising expenditure [23], and focused actions may to some extent alter $q$. Fig. 1 shows the adoption rate and cumulative sales when either the innovative behaviour or the word-of-mouth effect prevails (data is taken from the example in Section 3). From the viewpoint of marketing and finance, the innovative case seems to be preferable, since it leads to quickly exploit the firm’s market potential and to anticipate cash flow.

2.2. The side of manufacturing — learning effects

The presence of a demand peak due to diffusion effects is disturbing for production managers especially if, due to a prevailing innovative behaviour, it is located close to launch time. The demand peak exacerbates the trade-off between manufacturing capacity and backordering or lost sales, since building inventory up in advance becomes impossible, at least if not by postponing launch. In second instance, because of learning effects, manufacturing capacity is lower at the beginning of the product life cycle. The problem is similar to the one examined by Jaber and Bonney [12] but is made even more critical by the diffusion effect, which causes the demand peak.

2.3. Modelling the decision problem

Based upon the previous discussion, a discrete-time mathematical programming model has been developed, in order to study optimal policies related to both capacity planning and management. The parameters and variables are the following:

Parameters

$t = (1, 2, \ldots, T)$ index for time buckets.

$\beta$ learning factor, where $0 \leq \beta \leq 1$, and where $(1 - \beta)$ is the reduction in unit cost and time when cumulated production doubles.

$VC_0$ variable cost at product launch.

$VC_t$ variable cost at time bucket $t$, where

$$VC_t = VC_0 t^{\log_{10}(1 - \beta)}$$

(4)

which is an approximation to the general law governing learning phenomena, since it depends upon elapsed time and not upon cumulated production.

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Fig. 1. Demand dynamics under prevailing innovative and imitative effects.
FC fixed investment cost required to install a manufacturing “element” with initial capacity of one product unit per time bucket, i.e. before learning occurs. Overall investment is assumed to be linear with the number of such “elements” installed, thus revealing no increasing returns to scale, as is often the case in manufacturing operations. This assumption discourages over-investment in manufacturing facilities, thus increasing the significance of such a decision, if it should occur under an optimal policy.

MC<sub>t</sub> actual capacity at time <i>t</i> of an element with initial unitary manufacturing capacity (i.e. with learning), where

\[ MC_t = MC_0 t^{-\log_2(1 - \beta)}. \]

<i>i</i><sub>c</sub> annual interest rate.

<i>r</i> interest rate per time bucket, where

\[ r = (1 + i_c)^{1/k} - 1 \]

where <i>k</i> is the number of time buckets per year.

<sub>z</sub><sub>t</sub> discount factor for expenses and revenues occurring at time bucket <i>t</i>, where

\[ z_t = 1/(1 + r)^t. \]

<i>p</i> Bass coefficient of innovation.

<i>q</i> Bass coefficient of imitation.

<i>M</i> initial market potential for the firm.

<i>M</i><sub>res</sub> residual fraction of the market potential held by the firm, if launch occurs at the end of the planning horizon instead of the beginning.

<i>M</i><sub>j</sub> market potential for the firm if launch occurs at <i>j</i>, with <i>1 < j <= T</i>. <i>M</i><sub>j</sub> is assumed to be linearly decreasing with <i>j</i>:

\[ M_j = \left( \frac{T - j}{T - 1} \right)(M - M_{res}M) + M_{res}M. \]

Note that launching at <i>j</i> does not mean that the firm sells <i>M</i><sub>j</sub> units, but that it will supply what is left of the diffusion phenomenon, and its share of it will be a fraction <i>M</i><sub>j</sub>/<i>M</i> of what was initially available.

<i>D</i><sub><i>t</i><sub><i>j</sub></i></sub> demand for the firm at time bucket <i>t</i>, if launch occurs at time bucket <i>j</i>, where

\[ D_{tj} = M_j r(t) \quad \text{if} \quad t \geq j \]

\[ D_{tj} = 0 \quad \text{if} \quad t < j \]

where <i>r(t)</i> is given by (2). So, if the firm delays launch, this does not affect the diffusion phenomenon but only its share of it.

<i>SP</i> sales price per unit.

<i>h</i><sup>+</sup> inventory carrying cost per unit and per time bucket, approximated by

\[ h^+ = (r' + r)VC_0 \]

where <i>r’</i> represents other costs related to inventory (e.g. obsolescence, warehousing, insurance, etc.). <i>h</i><sup>+</sup> has been assumed to be proportional to the initial manufacturing cost and not to the actual cost incurred, which decreases because of learning.

<i>h</i><sup>−</sup> backorder cost, per unit and per time bucket.

<i>B</i> backordering penalty, per unit.

<i>VLSP</i> penalty associated with “voluntary” lost sales.

<i>ILSP</i> penalty associated with “involuntary” lost sales.

Decision variables

<i>MU</i> initial manufacturing capacity installed.

<i>P</i><sub><i>t</i></sub> units produced at time bucket <i>t</i>.

<i>B</i><sub><i>t</i></sub> backorders taken at time bucket <i>t</i>.

<i>VLS</i><sub><i>t</i></sub> voluntary lost sales at time bucket <i>t</i>.

<i>I</i><sub><i>t</i></sub> inventory level at time bucket <i>t</i>.

<i>I</i><sub><i>t</i></sub><sup>−</sup> backorder level at time bucket <i>t</i>.

<i>S</i><sub><i>i</i></sub><sup>+</sup> sales from inventory at time bucket <i>t</i>.

<i>S</i><sub><i>i</i></sub><sup>−</sup> backordered units delivered at time bucket <i>t</i>. 

<i>c</i> ratio between customers turned away by backlog and backorder level (i.e. if the latter at time bucket <i>t</i> are <i>I</i><sub><i>t</i></sub><sup>−</sup>, there will be <i>γI</i><sub><i>t</i></sub><sup>−</sup> “involuntary” lost sales due to impatient customers).
The model

\[
\text{max } \sum_{t=1}^{T} \left[ (S^+_t + S^-_t)z_t \right] - \text{FC MU}
\]

\[
- \sum_{t=1}^{T} z_t P_t V C_t - h^+ \sum_{t=1}^{T} z_t I^+_t - h^- \sum_{t=1}^{T} z_t I^-_t
\]

\[
- B \sum_{t=1}^{T} z_t B_t - \text{VLSP} \sum_{t=1}^{T} z_t \text{VLS}_t
\]

\[
- \text{ILSP} \sum_{t=1}^{T} z_t \gamma^+ I^-_t
\]

s.t.

\[
P_t \leq \text{MC}_t \text{ MU}, \quad \forall t = 1, \ldots, T, \quad (12)
\]

\[
I^+_t = I^+_{t-1} + P_t - S^+_t - S^-_t, \quad \forall t = 1, \ldots, T, \quad (13)
\]

\[
I^-_t = I^-_{t-1} + B_t - S^-_t, \quad \forall t = 1, \ldots, T, \quad (14)
\]

\[
\text{VLS}_t + B_t + S^+_t = \sum_{j=1}^{T} D_{ij} L_j - \gamma^+ I^-_t,
\]

\[
\forall t = 1, \ldots, T, \quad (15)
\]

\[
\sum_{t=1}^{T} L_j = 1, \quad (16)
\]

\[
\text{SI}_1, \text{DB}_1, P_1, I^+_1, I^-_1, \text{VLS}_1, B_1 = 0, \quad (17)
\]

\[
I^+_T, I^-_T = 0, \quad (18)
\]

\[
\text{MU} \geq 0, \quad (19)
\]

\[
\text{SI}_t, \text{DB}_t, P_t, I^+_t, I^-_t, \text{VLS}_t, B_t \geq 0, \quad \forall t = 1, \ldots, T, \quad (20)
\]

\[
L_j \in \{0, 1\}, \quad \forall j = 1, \ldots, T. \quad (21)
\]

The objective function (11) maximises discounted profits, obtained by subtracting from sales revenues the initial investment cost, variable manufacturing costs, inventory carrying costs, backordering costs and lost sales penalties. Constraint (12) reflects limitations in manufacturing capacity. Constraints (13) and (14) are status equations for inventory and backlog. Production, backordering, inventory and lost sales are balanced in constraint (15). Constraint (16) forces launch to occur at one date, and constraints (17) and (18) give initial and terminal conditions. Constraints (19)-(21) impose non-negativity or integrality of variables.

3. Experimental results

The model has been tested upon a case built with realistic data from the automotive industry, which could be representative of manufacturing capacity life-cycle issues for a medium-priced car, sold to distributors at 7.5 KECU. Parameters are reported in Table 1 and have mostly been drawn from trade journals and reports, while diffusion parameters are derived from [22] and learning parameters from Hiller and Shapiro [24]. The market potential has been assumed to be 1 700 000 units, over a 5 year life-cycle. Thirty time buckets have been used, which would be a coarse discretisation for industrial purposes, but is sufficient for the type of analysis being carried out here.

Parameters that have been supposed to have little influence upon optimal policies have been kept constant during all experiments. Six other parameters that could presumably have affected decision-making trade-offs in interesting ways have been placed at two different levels, named “low” and “high”. A “base” scenario has been selected, and related values are shown with asterisks in the table. These couples of values are somewhat extreme, and have been thus chosen in order to make the characteristics of optimal policies emerge with greater evidence. The conclusions that will be drawn from such policies therefore have to be taken as interpretations of trade-offs, but not as normative results, since actual industrial problems may be less extreme than the one used in the experimentation.

The experimentation has been carried out in three steps, as shown in Fig. 2. Parameters have been prepared with a spreadsheet, and the problem has then been run upon the LINGO optimisation software [25]. In Experiment A, diffusion effects have been neglected and demand has been considered constant at the average level $M/T$. Experiment B assumes the optimal capacity derived from Experiment A as a given (not as a decision variable), but demand is now modelled according to the
Bass diffusion process. Experiment C looks for optimal policies when demand is (correctly) modelled as a diffusion process and comparisons are eventually made between the results of the three experiments. Finally, Experiment D focuses upon capacity management policies, again by taking manufacturing capacity as given.

### 3.1 Experiment A

If a firm neglects the existence of a demand peak due to diffusion effects, the trade-off between manufacturing capacity and lost sales disappears. The optimal initial manufacturing capacity is slightly below the (assumed) constant demand level. The

<table>
<thead>
<tr>
<th>Parameter name</th>
<th>“Low” (L) or unique value</th>
<th>“High” (H) value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P )</td>
<td>7.5 KECU</td>
<td>—</td>
</tr>
<tr>
<td>( M )</td>
<td>1,700,000 units</td>
<td>—</td>
</tr>
<tr>
<td>( T )</td>
<td>30 time buckets (equivalent to 5 yr)</td>
<td>—</td>
</tr>
<tr>
<td>( r )</td>
<td>0.82%</td>
<td>—</td>
</tr>
<tr>
<td>( FC )</td>
<td>25 KECU per unit per time bucket</td>
<td>—</td>
</tr>
<tr>
<td>( VC_0 )</td>
<td>5.5 KECU</td>
<td>—</td>
</tr>
<tr>
<td>( \beta )</td>
<td>0.05</td>
<td>0.15 (*)</td>
</tr>
<tr>
<td>( \lambda )</td>
<td>5% (*)</td>
<td>15%</td>
</tr>
<tr>
<td>( p, q )</td>
<td>0.002, 0.54 (prevailing imitative effect)</td>
<td>0.083, 0.22 (prevailing innovative effect)</td>
</tr>
<tr>
<td>( M_{res} )</td>
<td>0%</td>
<td>50% (*)</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>5% (*)</td>
<td>25%</td>
</tr>
<tr>
<td>( \mu )</td>
<td>0.1 KECU per unit</td>
<td>0.25 KECU per unit (*)</td>
</tr>
<tr>
<td>( h^- )</td>
<td>0.075 KECU per unit and per time bucket</td>
<td>0.2 KECU per unit and per time bucket (*)</td>
</tr>
</tbody>
</table>

Fig. 2. Flow chart of experimentation carried out upon the model.
firm builds up some backlog for some time after launch since, thanks to learning, it expects capacity to increase with time. Experiment A has been run at the base scenario, and with six alternate scenarios obtained by changing parameters one at a time. Table 2 shows the learning parameter, $\beta$, has a significant effect upon optimal profits and initial manufacturing capacity. Figs. 3 and 4 detail such an effect for intermediate values of $\beta$.

### 3.2. Experiment B

Manufacturing capacity is now constrained to the value provided by Experiment A, but demand is now modelled according to a Bass diffusion process. Experiment B has been run in the scenarios used for Experiment A, in both cases of prevailing innovative and imitative phenomena. Fig. 4 shows that profits are now substantially lower than expected from Experiment A. The gap increases with the learning parameter since, the higher such parameter, the more the firm that neglects diffusion effects will under-invest in manufacturing capacity, and the more severe the consequences will be when encountering the sales peak. Table 3 shows that reduction in profits mostly occurs with large amounts of lost sales and backordering and, in some cases, with the decision to postpone launch. Such choice occurs in the case of innovative diffusion, combined with a low learning parameter or with a high fraction $\gamma$ of impatient customers. Finally, when innovative behaviour prevails, lower profits occur.

### 3.3. Experiment C

In Experiment C, demand is modelled according to the Bass model, and manufacturing capacity is taken as a decision variable. The firm is now free to choose manufacturing capacity, while (correctly) taking into account the diffusion phenomenon. Fig. 3 shows that optimal initial manufacturing capacity is considerably higher than in Experiment A, since the firm now expects the peak in demand and acts accordingly. Profits are higher than in Experiment B (Fig. 4), while the firm has fewer lost sales and backorders and is forced to postpone launch only once. Table 4 shows that, with
imitative diffusion, the firm manages the sales peak partly by building inventory up before it occurs, and partly by taking up some backorders when it has been depleted.

When switching among innovative and imitative diffusion profits are quite different, with the innovative scenario appearing less favourable. Prevailing innovative behaviour does not lead to a larger optimal manufacturing capacity, since the gain due to higher sales would be offset by the required investments. A firm facing an innovative diffusion phenomenon could therefore simply have to settle for a lower level of sales and profits. The results appear to be fairly independent from the penalties associated to losing sales, since they are in any case small when compared to unitary margins being lost.

3.4. Experiment D

The previous experiments have focused upon capacity planning, while Experiment D deals with the problem of managing this capacity over the product's life cycle. In order to highlight the related optimal policies, the problem has been strained by imposing an initial manufacturing capacity at a slightly lower level than the one recommended by Experiment C (50,000 units per time bucket, instead of around 70,000). Experiment D has been carried out for all of the $2^7 = 128$ combinations coming from the parameter levels in Table 1. For brevity, detailed results of Experiment D are not reported in the paper. In order to study the effect of parameters upon profits, the 128 scenarios were taken as if they were a full-factorial ANOVA experiment over the seven parameters, so to calculate the proportion of profit “variance” explained by each parameter and two-way combination of parameters (Fig. 5). The results show that the main factors leading to high profits are imitative diffusion, high learning parameter, low interest rate, and few impatient customers. The share of demand lost because of delayed launch (associated to $M_{res}$), appears to
have little importance in determining overall profits, even if these are lower indeed when launch is delayed. Lower profits connected with delayed launch could therefore be due to having missed the initial sales peak, rather than to having lost market share.

The optimal policy includes delaying launch when diffusion is predominantly innovative, the learning parameter is low and lost sales penalties are high. Backordering is a quite common policy in the experiments carried out. In a number of scenarios, it becomes the unique policy in that the firm does not keep any inventory, nor it has any voluntary lost sales. This happens with innovative diffusion, high learning parameter, many impatient customers and low backordering cost. Finally, voluntarily accepting lost sales for a long period of time (i.e. more than four time buckets) has been found to be an optimal policy when diffusion is predominantly innovative, there is a low learning parameter, a low lost-sales penalty and a high backordering cost. In this case, profits are generally quite low.

4. Managerial implications and conclusions

The experiments described in Section 3, with the restrictive hypothesis carried, showed the significance of the problem discussed in this paper. Interesting findings relate to both the topics covered, i.e. the planning and the management of manufacturing capacity.

Concerning capacity planning, the importance of the trade-off between lost sales and manufacturing capacity has been clearly shown, leading to the conclusion that firms that do not consider peak demand due to diffusion effects may under-invest in manufacturing capacity and experience reduced profits due to lost sales. Learning phenomena have been found to be an extremely important factor in mitigating the trade-off, thus suggesting that efforts
### Table 3
Summary of results in Experiment B

<table>
<thead>
<tr>
<th>Scenario</th>
<th>( \beta )</th>
<th>( i_e (%) )</th>
<th>VLSP [KECU]</th>
<th>( M_{res} )</th>
<th>( h^- ) (KECU/unit x time bucket)</th>
<th>Diffusion type</th>
<th>Delayed launch</th>
<th>Time buckets w/inventory</th>
<th>Time buckets w/backlog</th>
<th>Time buckets w/lost sales</th>
<th>Profits (MECU)</th>
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### Table 4
Summary of results in Experiment C

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<th>VLSP [KECU]</th>
<th>( M_{res} )</th>
<th>( h^- ) (KECU/unit x time bucket)</th>
<th>Delayed launch</th>
<th>Time buckets w/inventory</th>
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oriented towards continuous improvement in cost reduction and capacity increase have a strategic significance that goes beyond the figures they immediately influence [26]. Finally, it has been shown that the financial and marketing benefits connected to predominantly innovative diffusion may be neutralised by the problems cast upon manufacturing by the anticipated demand peak it causes.

Concerning policies for managing manufacturing capacity, experimentation has shown that there are five most influential parameters, which are the type of diffusion phenomena, the learning parameter, lost sales and backorder penalties and, finally, the fraction of customers that may be turned away by backorder levels. Predominantly imitative diffusion processes pose lesser management problems, and optimal policies have in these cases been found to be a combination of three basic choices, which are building inventory, relying on backorders, and accepting lost sales. Conversely, a firm facing an innovative diffusion process may have to opt for one of the three strategies summarised in Fig. 6.

The first strategy is suggested when lost sales penalties are high and the learning parameter is low. This case strains trade-off decisions, since it contemporarily increases the cost of not satisfying demand and delays the increase of manufacturing capacity due to learning. In this case, the firm may find it optimal to postpone launch and avoid...
competing during the initial sales peak, if this would only generate a large number of unsatisfied customers. The firm might instead accumulate inventory and launch the product when demand will have reached a level compatible with its manufacturing capacity.

The second strategy is connected with low backordering costs, a high number of impatient customers and a high learning parameter. In this case, the firm’s optimal policy may be that of using only backorders and serve those customers that are willing to wait. This strategy may be explained because many impatient customers automatically reduce the gap between peak demand and available capacity. If there is a low backorder cost for those customers that are willing to wait, it will be profitable to use capacity to serve these customers only. This might be the case in a market with differentiated brands, with a firm deciding to serve only brand-loyal customers accepting to wait, possibly because of a high brand image. Customers who do not value the brand, and for whom quick delivery is more important, would instead be turned away.

The third strategy is to accept a consistent amount of lost sales throughout the diffusion process. Our model suggests this policy when the lost sales penalty and learning parameter are low, and if backordering costs are high. This could be the case of commodity-like products, a case in which customers prefer switching among different manufacturers rather than waiting for delivery.

Further research may extend the discussion presented in this paper, using alternative research approaches if convenient. In first instance, pricing may be introduced as a decision variable. Advertising intensity too could be considered as a decision variable, thus altering the innovative parameter in Bass’ model. Both choices would lead to non-linear models, which would favour the use of optimal control techniques to derive and discuss strategies. This would also have the advantage of providing analytical, instead of numerical, results.

Further extensions could emerge by allowing manufacturing capacity to be expanded or reduced over the planning horizon, eventually in different locations, or to consider the allocation of capacity to a specific product within a flexible manufacturing facility [27]. Other extensions could consist in considering substitution between subsequent product generations and phased product launch in different markets, which could help to smooth the initial demand peak. Finally, empirical evidence could be sought in order to verify the optimality of the policies thus identified.

References


