A genetic algorithms approach to growth phase forecasting of wireless subscribers

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Abstract

In order to effectively make forecasts in the telecommunications sector during the growth phase of a new product life cycle, we evaluate performance of an evolutionary technique: genetic algorithms (GAs), used in conjunction with a diffusion model of adoption such as the Bass model. During the growth phase, managers want to predict (1) future sales per period, (2) the magnitude of sales during peak, and (3) when the industry would reach maturity. At present, reliable estimation of parameters of diffusion models is possible, when sales data includes the peak sales also. Cellular phone adoption data from seven Western European Countries is used in this study to illustrate the benefits of using the new technique. The parameter estimates obtained from GAs exhibit good consistency comparable to NLS, OLS, and a naïve time series model when the entire sales history is considered. When censored datasets (data points available until the inflection point) are used, the proposed technique provides better predictions of future sales; peak sales time period, and peak sales magnitude as compared to currently available estimation techniques.

Keywords: New product diffusion-estimation; Genetic algorithms; Telecommunication industry; Bass model

1. Introduction

The telecommunication industry has experienced rapid growth in the recent years and is forecasted to exceed $790B in revenues by 2003 (2000 Multimedia Telecommunications Forecast). Specifically the sales of mobile wireless phones worldwide increased by 46% in year 2000. Also, by the end of 2001, European Mobile Communications (EMC) forecasts world cellular subscriptions to top the one billion mark, up from 728 million at year end 2000. The sustained tremendous growth in the wireless communications industry over the past decade also aggravates the need for accurate forecasts of future growth potential. The ubiquitous product life cycle would suggest that a phase of consolidation and decline in growth is imminent. In that case, when is it supposed to happen?

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Sales forecasts during the early stages of a product life cycle are critical to both new product managers and academicians. The growth phase of the product life cycle is characterized by high growth in sales and market expansion. Also, the marketing strategy in the growth phase is characterized by heavy advertising as compared to heavy promotions in the maturity/decline stage (Kotler, 2000). Given the implications to marketing strategy, predicting the future sales during the growth phase is of paramount importance. In addition to predicting the future sales of the product, managers need to know when the product would reach maturity and what the value of sales would be at maturity. Accurate knowledge about the time to peak sales helps managers deduce the growth rate of their markets, and the marketing mix necessary to accelerate the sales of their new innovation. Appropriate forecasts of future growth potential are essential for proper management of resources, and further have important profit implications.

Several micro-level telecommunications demand models have been proposed (Fildes, 2002) that accommodate characteristics such as network effects, price elasticity, government regulations, incentive structures and product quality. The micro-level models seem to work well in established markets and for new products/services the reliance is more on qualitative measures such as expert/consumer opinion. In addition to micro-level models, managers are also interested in forecasting the macro-level growth for a new market over a fixed time horizon in order to assist decision-making and strategy development. The macro-level models that are used need to be parsimonious and are mostly used in combination with micro-level models for decision-making. Several macro-level time series models including logistic growth curves have been proposed to predict the future category level sales of an innovation. The Bass (1969) model is one such model that uses just the time since a product has been introduced in the market for making reliable forecasts of the future sales of the innovation. In addition to providing reliable forecasts, the Bass model has attractive behavioral implications regarding customer motivation that could assist managerial decision-making.

Since its introduction, the Bass (1969) model of innovation adoption has spawned a wide range of applications and models that explain the rate of adoption of an innovation (Bayus, 1992), the effect of marketing mix variables on the market potential and rate of adoption of an innovation (Bass, Krishnan, & Jain, 1994; Jain & Rao, 1990; Kalish, 1983; Bass, 1980; Robinson & Lakhani, 1975), and diffusion of innovations in multiple markets (Krishnan, Bass, & Kumar, 2000; Kumar, Ganesh, & Echambadi, 1998; Takada & Jain, 1991). Even the basic Bass diffusion model has been modified to accommodate for time-varying parameters, flexibility in the shape of the diffusion pattern, and evaluating marketing strategies that are effective in various stages of the product life cycle, and influence of another country on one country’s diffusion (Kumar & Krishnan, 2002; Ganesh, Kumar & Subramaniam, 1997). Forecasting of future sales, a critical application of the Bass diffusion model, has received little or no attention because researchers are faced with difficulties in using the Bass model for this purpose (Parker, 1994). The forecasting of future sales of a new product before the inflection point in the product life cycle is reached is a particularly critical drawback (Mahajan, Muller, & Bass, 1990).

Ordinary Least Squares (OLS), Maximum Likelihood, and Non-linear Least Squares (NLS) procedures have been proposed in the literature for estimating the parameters in a Bass diffusion model. However each technique has its own shortcomings with respect to providing reliable and accurate forecasts of product sales/growth. The estimates based on OLS are biased
because OLS (1) assumes a discrete process for data generated from a continuous process, (2) suffers from multicollinearity, and (3) does not generate standard errors directly for \( p \), \( q \), and \( m \) which makes testing hypotheses impossible. The estimates based on maximum likelihood are efficient in reducing sampling errors associated with survey-based data but are not efficient in reducing errors related to measuring exogenous factors such as marketing mix. The NLS estimates suffer from ill-conditioning (Van den Bulte & Lilien, 1997), which makes the estimates proportional to the number of data points available for estimation. Van den Bulte and Lilien (1997) and Srinivasan and Mason (1986) show that the estimates of the Bass model (derived from Non-linear Least Squares) are biased (or in most cases do not converge) when used for making predictions regarding future sales during the growth phase of the product life cycle. Also, the estimates obtained are correlated to the number of data points used for estimation. Specifically, the estimate of market potential, \( m \), is downward biased when fewer data points are used for estimation and vice-versa for the coefficient of imitation \( q \). This bias and systematic change in parameter estimates is attributed to ill-conditioning—a problem that exists in intrinsically non-linear models that are estimated using Non-linear Least Squares (NLS) (Seber & Wild, 1993; Van den Bulte & Lilien, 1997; Venkatesan, Krishnan, & Kumar, 2001). These issues associated with the widely adopted NLS technique for estimation of the Bass model have left forecasters with few ‘rules-of-thumb’ or empirical generalizations to work with.

In the discrete version of the Bass model (OLS estimation) and in a majority of the cases, there is no restriction on the number of data points required for estimation. However, with OLS the estimates of the Bass model cannot be bounded and in a majority of the cases the estimates obtained with fewer data points are unreliable. In the continuous time framework, the reliable estimation of the Bass model is possible only when the inflection point in the product life cycle is available for estimation. Hence, the utility of the Bass model is constrained by lack of appropriate estimation techniques and is currently used primarily for retrospective analysis. By the time sufficient observations have been collected for reliable estimation, it is too late to use the estimates for forecasting purposes (Mahajan et al., 1990).

Current forecasting techniques, based on the Bass model, in general require educated guesses from managers about either (1) the eventual market potential of a product \( (m) \), (2) time of the peak of the non-cumulative adoption curve, and (3) the sales at the peak time period (Mahajan & Sharma, 1986), or (1) the eventual market potential of a product \( (m) \), (2) the sales during the first time period, and (3) an estimate of the sum of the coefficient of innovation \( (p) \), and the coefficient of imitation \( (q) \) (Lawrence & Lawton, 1981). The initial guesses are based on data from industry reports, surveys, test-marketing sales and from diffusion estimates of analogical products. In a review of models available for forecasting diffusion of innovations, Meade and Islam (2001) conclude that current evidence suggests that judgmental estimates of market potential contribute little to the accuracy of forecasts of future sales. The econometric procedures used for estimating the Bass model such as Ordinary Least Squares (OLS) (Bass, 1969), Maximum Likelihood estimation (Schmittlein & Mahajan, 1982), and Non-linear Least Squares (NLS) (Srinivasan & Mason, 1986) have individual drawbacks and are all not useful for generating forecasts during the growth phase of the diffusion curve. Hierarchical Bayes procedures to predict the sales of new products before peak sales are weak when the new product takes time to take off, or in other words is left skewed (Lenk & Rao, 1990).

In this study, we evaluate the performance of
a simple simulation based search technique—Genetic Algorithms (GAs)—for forecasting the magnitude of future sales, time period to peak sales, and the value of sales during peak time period using the Bass model when only a few data points are available, i.e., well before the inflection point for the new product is reached. GAs are parallel search algorithms that are based on an analogy with Darwin’s theory of evolution to converge to a global minimum in a given search space. The inherent nature of GAs ensures that the estimates are robust even with a small number of data points irrespective of the functional form of the objective function. These features of GAs make them an excellent candidate for forecasting purposes, with non-linear models such as the Bass model. In order to establish the reliability and validity of estimates generated from GAs, and to evaluate the utility of the estimates for hypotheses testing, the performance of GAs is compared with techniques such as NLS and OLS and the finite sample properties of the estimates from GAs are also derived.

In the next section we provide an overview of past research in forecasting sales using Bass models, in Section 3 we provide a simple description of genetic algorithms, Section 4 explains the design and results of the study which compares the performance of GAs, NLS and OLS in forecasting the time to peak sales for cellular phones in seven different countries in Western Europe, finally the conclusions, limitations, and future research directions are provided in Section 5.

2. Conceptual background

2.1. Model formulation

We choose to use the Srinivasan and Mason (1986) operationalization, which can be represented as

\[ X(t) = m[F(t) - F(t - 1)] + \epsilon \]  

(1)

\[ F(t) = \frac{1 - e^{-(p+q)t}}{1 + (q/p)e^{-(p+q)t}} \]  

(2)

where \( X(t) \) = sales at time \( t \), \( m \) = number of eventual adopters, \( F(t) \) = cumulative distribution of adoptions at time \( t \), \( p \) = coefficient of innovation, and \( q \) = coefficient of imitation. \( \epsilon \) = normally distributed random error term with mean zero and variance \( \sigma^2 \).

The density function \( f(t) \) or each period sales is obtained by differentiating (2) with respect to \( t \),\( (\text{i.e.,}) \)

\[ f(t) = \frac{(p+q)^2}{p} e^{-(p+q)t} / (1 + (q/p)e^{-(p+q)t})^2 \]  

(3)

Finally, the time to peak period sales \( (T^*) \) is obtained by differentiating (3) and solving for \( t \), which yields

\[ T^* = \frac{1}{(p + q)} \ln(q/p) \]  

(4)

The level of sales at peak is given by substituting 4 in 3, \( (\text{i.e.,}) \)

\[ X(T^*) = m \times (1/(4q))^*(p + q)^2 \]  

(5)

The inflection point for each period sales is obtained by differentiating (3) twice, with respect to \( t \), and solving for \( t \), which yields,

\[ T_{\text{left}}^{**} = \frac{1}{p + q} \ln \left( \frac{q}{p} \right) \times (2 - \sqrt{3}) \]  

(6a)

\[ T_{\text{right}}^{**} = \frac{1}{p + q} \ln \left( \frac{q}{p} \right) \times (2 + \sqrt{3}) \]  

(6b)

It is useful to note here that the time for peak period sales depends only on the hazard rate parameters \( p \) and \( q \), and is independent of the market potential \( m \). This is also intuitive if we believe that the hazard rate determines the shape of the diffusion curve and hence also determines the time of peak sales. The market potential term, \( m \), provides only the level effect to the diffusion curve and it is useful for predicting the

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\(^1\)Please refer to Fildes (2002) for a discussion of various model formulations for the Bass model.
sales at $T^*$. In order to obtain reliable estimates of $p$, $q$, and $m$ before the peak sales is reached data is required until $T_{\text{left}}^{**}$; which represents the take-off period for any new product.

2.2. Forecasting with commonly employed estimation techniques

The shortcomings associated with the current estimation techniques (as explained earlier) have led researchers to adopt subjective techniques for forecasting adoption of new product acceptance as described below. Current procedures to forecast future sales, time to peak period, sales at the peak period of new products hence involve variations of the following steps (Lawrence & Lawton, 1981; Mahajan & Sharma, 1986; Modis & Debecker, 1992):

- Managers make an educated guess about the parameters $a$ (coefficient of external influence: $p$), $b$ (coefficient of internal influence: $q$) and $m$ (market potential).
- These are then used to derive the diffusion curve algebraically.
- Once the first year sales data ($N(1)$) becomes available, the value of $a$ can be updated as: $a = N(1)/m$
- The diffusion curve is derived again using the updated parameters.
- As more data becomes available the forecasts are revised or updated based on techniques such as the adaptive Bayesian feedback filter.

The estimate for market potential can be obtained from pre-launch purchase intention measures (Jamieson & Bass, 1989). The estimates for $p$ and $q$, however, need to be based on management judgment or based on estimates from analogical products. Lenk and Rao (1990) suggest a Hierarchical Bayes procedure to obtain initial estimates (priors) of $p$ and $q$, based on product sales for similar new product adoption curves. As sales data for the new product is obtained the initial prior estimates are updated with the new information to form posterior estimates of the new product sales. The updating procedure resembles a weighted sum of the initial estimates from similar products and estimates derived from the new sales data. During the early stages of the product life cycle, the initial estimates from sales of similar products carry more weight but as more new information is obtained, i.e., later in the product life cycle, the estimates based on sales of the new product carry more weight. The strength of the Hierarchical Bayes procedure lies in accommodating the heterogeneity between and within product sales curves when obtaining initial estimates. However, estimates from these procedures are not accurate when the new product diffusion curve is skewed away from the near symmetric Bass model assumption.

Subjectivity involved in the above procedures has led researchers to conclude that “parameter estimation for diffusion models is primarily of historical interest; by the time sufficient observations have been developed for reliable estimation, it is too late to use the estimates for forecasting purposes” (Mahajan et al., 1990). Hyman (1988) also concluded similarly that waiting for enough observations to fit the correct model renders the benefits of the forecasting exercise a moot issue.

Considering the significant advantages of accurate forecasts of product life cycle stages, we propose a scientific method, Genetic Algorithms, to estimate the diffusion model and forecast the diffusion curve of a new product once a minimum number of data points becomes available (about 4–5 data points). Given the subjectivity involved in current techniques this is a significant contribution to both the literature and the practitioners. Even a small increase in the accuracy of prediction can result in a significant increase in profits for the organization. This fact is even more critical given that even a small change in the parameters $p$ and $q$ can generate significantly different diffusion curves. In the next section, we discuss
3. Genetic algorithms

As posited by Goldberg (1989), Genetic Algorithms are search algorithms based on the mechanisms of natural selection and natural genetics. In other words, the genetic algorithm iterates toward a global solution through a process that in many ways is analogous to the Darwinian process of natural selection.

Given a specified optimization problem, the algorithm starts with the initial set (population hereafter) of random candidate solution vectors (the first generation) and then selects a subset of the population to contribute offsprings to the next generation of candidate solution vectors. The key to this process is selectivity. Not all population members are given an equal chance of contributing offspring to the next generation so that only a select few actually contribute. In particular, population members most likely to contribute are those possessing traits favorable to solving the optimization problem; least likely to contribute are those possessing unfavorable traits. For example, if the solution vector consists of parameter estimates for a diffusion model, solution vectors that minimize the sum of squares of errors (SSEs) are more likely to be selected than others. In this way, a new population of candidate solutions (the second generation) is built from the most desirable traits of the initial population. The power of genetic algorithms rests on the operations that are performed on the new population. Just as in natural systems where the children inherit traits from both their parents, in genetic algorithms a candidate solution vector in the new generation has two parent solution vectors selected from the previous generation and operations such as crossover and mutation (explained later) performed on the offspring ensure that the new solution vector inherits traits from both its parent solution vectors. Thus, as iterations continue from one generation to the next, traits most favorable to reaching a solution thrive and grow, but those least favorable die out. Eventually, the initial population evolves to one that contains a solution to the optimization problem and the iterations terminate.

The genetic algorithm has two main limitations. First, a genetic-algorithm search can entail many evaluations of the objective function and, consequently, much execution time. This is a significant problem with large datasets. However, the Bass (1969) model uses annual sales data and a typical sample size is around 15–20. Also, given the present rate of progress in computer technology the required computational expense is most likely a temporary limitation. The second limitation is that, like other direct search methods, convergence of the genetic algorithm does not necessarily occur at a single optimum solution. The search will typically find a point that is close enough to the maximum. A gradient-type algorithm can then be used along with the genetic algorithm so as to efficiently converge to the maximum. The genetic algorithm is best viewed as a potentially valuable complement rather than a substitute for traditional algorithms. The complexity of coding involved in implementing genetic algorithms is a major impediment to its widespread applicability. However, many software packages (GA toolboxes for use with MatLab, S-Plus, C++, and Excel) are being released with wide-ranging functions and applications of genetic algorithms built into them that can be run even in commonly used spreadsheets.

3.1. How the algorithm works

The mechanics of a simple genetic algorithm are surprisingly simple, involving nothing more complex than copying solution vectors (strings) and swapping partial solution vectors (strings). Simplicity of operation and power of effect are
two of the main attractions of the genetic algorithm.

A simple genetic algorithm that yields good results in many practical problems is composed of three operators: reproduction, crossover, and mutation. A genetic algorithm iterates through the following three steps (Fig. 1 illustrates the cycle of steps in a Genetic Algorithm):

1. **Reproduction** is a process in which individual strings of a generation (parent generation) are copied to the next generation (child) according to their objective function values, \( f \). Intuitively, we can think of the function \( f \) as some measure of profit, utility, or goodness that we want to maximize. Copying strings according to their fitness values means that strings with a higher value have a higher probability of contributing one or more offspring in the next generation. The probabilities could depend on the proportion of solutions present in a parent generation, based on linear ranking system of the solutions or based on a tournament selection. This operator is an artificial version of natural selection, a Darwinian survival of the fittest among string creatures.

2. After reproduction, simple **crossover** may proceed in two steps. First, members of the newly reproduced strings (or new generation) are paired at random. Second, each pair of strings undergoes crossing over as follows: an integer position \( K \) along the string is selected uniformly at random between 1 and the string length less one \([1, l - 1]\). Two new strings are created by swapping all characters between positions \( K + 1 \) and \( l \). This process is explained in Fig. 2.\(^4\). The mechanics of reproduction and crossover are surprisingly simple, involving random number generation, string copies, and some partial string exchanges. Nonetheless, the combined emphasis of reproduction and the structured, though randomized, information exchange of crossover give genetic algorithms much of their power.

3. **Mutation** is the process of randomly changing a cell in the string or the solution vector. Mutation is the process by which the algorithm attempts to ensure a globally optimal solution. If the algorithm is trapped in a local minimum, the mutation operator randomly shifts the solution to another point in the search space, thus removing itself out of the trap.

\(^4\)In the case of the Bass model, during cross over, the parameters in a new iteration are verified for validity (such negative values or values greater than one in the case of \( p \) and \( q \)). New solutions that do not satisfy the criterion are rejected.

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![Fig. 1. GA cycle of reproduction.](image-url)
The above steps are repeated until the algorithm is halted. The decision to halt the program can depend either on a prefixed number of generations, the time elapsed in the evolutionary process or the difference in solutions produced between two generations. These options are available in current software packages. The composition of the final generation of strings—the best strings—is the genetic algorithm’s solution to the problem. It should be noted that when new strings are created the old ones (those belonging to the previous generation) are discarded. Since the reproduction process tends to choose the ‘fittest’ members of a generation, the generations tend to evolve. Thus, an initial population of relatively undistinguished solutions evolves to yield the optimal solution in the final generation.

The operations crossover and mutation are not performed for every reproduction. The probability of a string being selected for crossover is proportional to the string’s fitness. Each operation is assigned a particular probability of occurrence or application. For example, if the probability of crossover is 0.6, out of every 100 strings only 60 strings undergo crossover. Likewise, if the probability of mutation is 0.033, out of every 100 strings only 3 strings undergo mutation. The probability of mutation is always very low, since the primary function of a mutation operator is to remove the solution from a local minimum. The probabilities are assigned based on the characteristics of the problem. For example, if the problem is characterized by a turbulent environment (i.e. if the solution space is not uniform all over) the probability of crossover and mutation are chosen to be high.

4. Design and results of study comparing forecasts

4.1. Asymptotic properties of the estimates from GA

The finite sample properties of GA estimates are established by conducting a Monte Carlo

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5The package ‘Evolver’ is used for estimation using GAs. Evolver is an Excel based add-on package distributed by Palisade Inc., for conducting analysis using genetic algorithms.
simulation study on the three datasets used in Bass et al. (1994), namely color television, air conditioners and clothes dryer. The desirable properties of the estimates from a non-linear least squares routine include (1) approximate normal distribution, and (2) variance of $\beta = 2\sigma^2(d^2 f(x, \beta)/d\beta^2)^{-1}$ (Griffiths, Hill, & Judge, 1993). The estimates from GA are reliable if they exhibit these properties of estimates from non-linear least squares. The investigation of the asymptotic properties of the estimates from GA is important for deriving inferences based on the estimates from GA. If the estimates from GAs exhibit properties similar to estimates from least squares, the tests such as $t$-test, and $F$-test hold for the estimates of GA also.

We use the datasets used in Bass et al. (1994) to establish asymptotic properties because these datasets have sales data well after the peak sales time period. The Monte Carlo simulation is performed as follows:

(a) For each dataset the estimation procedure is repeated 1000 times to obtain a matrix of 1000 estimates each of $p$, $q$, and $m$ for every dataset, resulting in a total of 3000 cells in each matrix.

(b) The values of $p$, $q$, and $m$ are then plotted as a histogram to test for their consistency and distributional properties.

These estimates are then compared with the estimates obtained from the NLS for the corresponding datasets.

4.2. Results

The results of this study are outlined in Table 1. As can be seen from this table, estimates obtained from GAs closely replicate the estimates from NLS in all the datasets. The distribution of parameter estimates from GAs for a sample dataset (color television) is provided in Fig. 3. The Figure shows that the estimates obtained from GAs are normally distributed and have acceptable standard deviations that are proportional to the asymptotic standard deviations obtained from the NLS method. Thus, it can be inferred that the parameter estimates obtained from GAs are consistent and have the desirable properties of standard statistical techniques.

4.3. Predicting future sales

4.3.1. Parameter comparison with simulated datasets

Fifty datasets were simulated for the purpose of understanding the performance of GA as compared to NLS and OLS when both full and

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Table 1
Estimates From GA and NLS for the asymptotic properties study

<table>
<thead>
<tr>
<th>Product</th>
<th>$p$</th>
<th>$q$</th>
<th>$m$</th>
<th>$p$</th>
<th>$q$</th>
<th>$m$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Color television</td>
<td>0.008</td>
<td>0.545</td>
<td>44,200</td>
<td>0.005</td>
<td>0.644</td>
<td>39,524</td>
</tr>
<tr>
<td>($n = 10$)</td>
<td>(0.0001)</td>
<td>(0.04)</td>
<td>(2337)</td>
<td>(0.0011)</td>
<td>(0.0447)</td>
<td>(1404)</td>
</tr>
<tr>
<td>Clothes dryer</td>
<td>0.013</td>
<td>0.327</td>
<td>16,661</td>
<td>0.013</td>
<td>0.332</td>
<td>16,239</td>
</tr>
<tr>
<td>($n = 13$)</td>
<td>(0.0001)</td>
<td>(0.04)</td>
<td>(1696)</td>
<td>(0.0023)</td>
<td>(0.0373)</td>
<td>(1011)</td>
</tr>
<tr>
<td>Air conditioner</td>
<td>0.010</td>
<td>0.361</td>
<td>19,276</td>
<td>0.009</td>
<td>0.380</td>
<td>18,320</td>
</tr>
<tr>
<td>($n = 13$)</td>
<td>(0.0001)</td>
<td>(0.04)</td>
<td>(1396)</td>
<td>(0.0021)</td>
<td>(0.0417)</td>
<td>(1122)</td>
</tr>
</tbody>
</table>

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*a* The values in parentheses below the reported estimates represent standard errors of the estimates, and $n$ = sample size.

*b* The reported estimates are means over 1000 repeats.
Fig. 3. Distributions of parameter estimates from GA for color television.
Table 2
Reproduction of model parameters: results from the simulation study

<table>
<thead>
<tr>
<th>True values</th>
<th>Full data (sample size $T = 17$)</th>
<th>Censored dataset (sample size $t = 7$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p$</td>
<td>$q$</td>
<td>$m$</td>
</tr>
<tr>
<td>NLS</td>
<td>0.030</td>
<td>0.380</td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.008)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>GA</td>
<td>0.030</td>
<td>0.380</td>
</tr>
<tr>
<td>(0.003)</td>
<td>(0.008)</td>
<td>(10.280)</td>
</tr>
</tbody>
</table>

*Reported values are means of the estimates obtained over 50 repeats. Values in parentheses are their respective standard deviations. The peak data point is observed at $t = 10$.

*NA—Not applicable because the estimates are biased.

censored data points are used. The datasets were simulated using the Srinivasan and Mason (1986) operationalization and a proportional Normal error structure with variance of 0.600. The parameter estimates for the simulation study were set at $p^* = 0.030$, $q^* = 0.380$ (mean estimates reported by Sultan et al. (1990) in their meta-analysis of diffusion studies), and $m^* = 1000$. For each of the fifty datasets, the diffusion curve was simulated for 17 time periods. On average, the peak for the diffusion curve occurred around $t = 10$. The results of the simulation study are provided in Table 2. As can be seen from Table 2, the estimates from GA ($p = 0.030$, $q = 0.370$, $m = 1015$) are similar to the estimates obtained from NLS ($p = 0.026$, $q = 0.410$, $m = 972$) when full datasets are used. Also, the estimates from both the techniques closely resemble the true values ($p^*$, $q^*$, and $m^*$) used to simulate the datasets. The datasets were censored around $t = 7$ such that there is no incidence of the peak time period in the censored datasets. The estimates from GA ($p = 0.034$, $q = 0.370$, $m = 950$), based on the censored datasets, are more accurate (in other words closer to the true values) than the estimates from NLS ($p = 0.030$, $q = 0.600$, $m = 620$).

4.3.2. Comparison of forecasts with simulated datasets

In the previous experiment we compared the capability of GA and NLS in reproducing the true parameter estimates of $p$, $q$, and $m$ from simulated datasets. We also conducted another simulation experiment to compare the forecasting ability of GA, NLS, OLS, and a naïve moving average technique. We created a simulated dataset from the Bass model with the true parameter estimates of $p^* = 0.008$, $q^* = 0.280$, and $m^* = 100$. We added a proportional error variance of 0.600 to the resulting sales data and generated data up to 20 time periods. We censored the datasets at $t = 9$ until $t = 19$ in order to compare the one-step ahead to eleven-step ahead forecasts from the above four methods. Specifically, for the eleven step ahead forecast, we censored the data at $t = 9$. Based on the estimates from the censored data, we forecast the rest of the data points ($t = 10$ until $t = 20$). The MAE is calculated as the difference

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*We used a variance of 0.600 because this is the commonly found error variance in a majority of empirical datasets. Also, Van den Bulte and Lilien (1997) use a similar error variance in the Monte Carlo simulation regarding diffusion data.

The forecasted sales in next period based on the moving average is calculated as the average sales from the year of introduction until the current year.

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between the forecasted values and the observed values in the holdout sample. For the one-step ahead forecasts, the data is first censored at \( t = 9 \). Based on the estimates from the censored dataset, we forecast the sales at \( t = 10 \). The absolute difference between the predicted sales for the next time period, \( t = 10 \) and observed sales at \( t = 10 \) is calculated. The above process is repeated by advancing the censoring point by one step (i.e., censoring point \( t = 10, 11, \ldots, 19 \) and calculating the absolute difference between the forecasted values in the next period (i.e. \( t = 11, 12, \ldots, 20 \)) and the observed values. The mean of the calculated absolute errors gives the MAE for one step ahead forecasts. The above process can be repeated for two steps ahead and so forth. The peak period (\( t^* \)) in the simulated dataset occurred at the 13th time period. The forecasting performance was assessed using the Relative Absolute Error (RAE) measure. The results of our experiment are provided in Table 3. As can be seen from Table 3, the forecasts based on GA are clearly better than NLS, OLS or a moving average measure. The moving average measure performs better than either NLS or OLS for forecasting horizons greater than four steps ahead. One possible reason for this could be that both NLS, and OLS require the peak time period in order to provide reliable estimates. In other words, both NLS and OLS required at least 14 data points (with respect to our experiment) to provide reliable estimates. The forecasting horizons of five steps ahead or more were generated from datasets with less than 13 data points. This is reflected in the poor RAE measures for NLS and OLS for forecasting horizons greater than four steps ahead. Overall, the estimates from GA are much more reliable for forecasting sales as compared to NLS, OLS or a naive moving average method. The simulation analysis hence establishes the utility of GA in forecasting future sales when the dataset does not contain peak sales. In the following analyses, we investigate the utility of GA in real empirical datasets.

5. Empirical analyses and validation of forecasts

Sales data on cellular phones in seven western European countries—Norway, Denmark,

<table>
<thead>
<tr>
<th></th>
<th>RAE</th>
<th>RAE</th>
<th>RAE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GA vs. NLS</td>
<td>GA vs. OLS</td>
<td>GA vs. moving average b</td>
</tr>
<tr>
<td>One step ahead</td>
<td>0.697</td>
<td>0.492</td>
<td>0.318</td>
</tr>
<tr>
<td>Two step ahead</td>
<td>0.463</td>
<td>0.367</td>
<td>0.304</td>
</tr>
<tr>
<td>Three step ahead</td>
<td>0.214</td>
<td>0.261</td>
<td>0.280</td>
</tr>
<tr>
<td>Four step ahead</td>
<td>0.112</td>
<td>0.125</td>
<td>0.240</td>
</tr>
<tr>
<td>Five step ahead</td>
<td>0.057</td>
<td>0.037</td>
<td>0.169</td>
</tr>
<tr>
<td>Six step ahead</td>
<td>NA</td>
<td>NA</td>
<td>0.133</td>
</tr>
<tr>
<td>Seven step ahead</td>
<td>NA</td>
<td>NA</td>
<td>0.153</td>
</tr>
<tr>
<td>Eight step ahead</td>
<td>NA</td>
<td>NA</td>
<td>0.159</td>
</tr>
<tr>
<td>Nine step ahead</td>
<td>NA</td>
<td>NA</td>
<td>0.133</td>
</tr>
<tr>
<td>Ten step ahead</td>
<td>NA</td>
<td>NA</td>
<td>0.144</td>
</tr>
<tr>
<td>Eleven step ahead</td>
<td>NA</td>
<td>NA</td>
<td>0.029</td>
</tr>
</tbody>
</table>

NA = Reliable estimates were not possible for NLS/OLS. Hence the RAE measure is not applicable.

a The total data length is \( T = 20 \). The peak data point occurs at \( t = 13 \). The censoring of datasets begin at \( t = 9 \) until \( t = 19 \).

b Moving average is based on the average of sales values from the two years prior to the censoring data point.
Finland, Germany, United Kingdom, France, and Italy, are used to evaluate the forecasting accuracy of the estimates obtained using GA, NLS, and OLS on the Bass model and the estimates from a time-series model. The data were gathered from published sources such as Merchandising Week, Census Reports, Euromonitor and other trade publications. The data obtained from these sources represent the number of cellular phone account subscriptions each year. Data are available from 1981 until 2000 for the countries used in this database and the peak time period ranges from 1993 (Finland) to 1996 (Italy). The diffusion curve for a representative country (Finland) is provided in Fig. 4. The analysis is performed on both the full datasets and on right censored data sets such that the censored data sets do not contain the peak period sales but contain enough data points to obtain reasonable estimates. In other words the Bass model can provide estimates even when only three data points are available. However, the estimates from the Bass model are not robust until data representing the left inflection point is available in the dataset. Hence, the datasets are censored such that the each dataset contains data up until the left inflection points. The data points included in each censored dataset and the point to peak sales is provided in Table 4. The censored datasets can be considered as calibration datasets, and the information available after the censoring time period are used as holdout samples for testing forecasting accuracy. The peak time period reported in the third column of Table 4 represents the observed empirical time of peak sales in each country.

While it is possible that a given person may open multiple accounts with a service provider, it is reasonable to assume that an individual would use only a single cellular phone. Relatives or close friends normally use the other accounts. Hence, the unique nature of the industry allows us to alleviate the problem of replacement purchases associated with sales data.
Table 4
Censored data lengths and peak time period for cellular adoption

<table>
<thead>
<tr>
<th>Country</th>
<th>Start year</th>
<th>Peak year</th>
<th>Censored data length</th>
<th>Holdout</th>
</tr>
</thead>
<tbody>
<tr>
<td>Germany</td>
<td>1984</td>
<td>1995</td>
<td>8 (1984–91)</td>
<td>8</td>
</tr>
<tr>
<td>Italy</td>
<td>1985</td>
<td>1996</td>
<td>8 (1985–92)</td>
<td>7</td>
</tr>
</tbody>
</table>

* Values in parentheses represent the years used in the calibration sample.

5.1. Results from using Bass model on the full and censored datasets

The estimates from GA, NLS and OLS were obtained based on both the full and censored datasets. The estimates from all three techniques are provided in Tables 5 and 6. With respect to full datasets, the estimates from GA provide better fit (measured in terms of Mean Absolute Deviation) to the datasets as compared to the estimates from NLS and OLS. The mean absolute deviation (MAD) of the estimates from GA is less than the MAD of the estimates from NLS and OLS for all the seven datasets analyzed. When full datasets are used, as revealed in a previous analysis (Table 1), the estimates from GA, NLS and OLS are similar, except that there is a consistent downward bias in the estimates of \( m \), from OLS. The above results show that while GA estimates are similar to estimates from other techniques, they also provide better fit to the data.

With respect to censored datasets, the estimates from NLS converge for only two (Norway and Denmark) of the seven countries used. The estimates from OLS make sense for four

Table 5
Estimates from GA and NLS when full datasets are used

<table>
<thead>
<tr>
<th>Country</th>
<th>GA estimates ( a )</th>
<th>NLS estimates</th>
<th>OLS estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( p )</td>
<td>( q )</td>
<td>( m )</td>
</tr>
<tr>
<td>Norway</td>
<td>0.003</td>
<td>0.300</td>
<td>4668</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.004</td>
<td>0.300</td>
<td>3640</td>
</tr>
<tr>
<td>Finland</td>
<td>0.003</td>
<td>0.380</td>
<td>4151</td>
</tr>
<tr>
<td>Germany</td>
<td>0.002</td>
<td>0.440</td>
<td>15203</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>0.004</td>
<td>0.320</td>
<td>22771</td>
</tr>
<tr>
<td>France</td>
<td>0.003</td>
<td>0.370</td>
<td>8911</td>
</tr>
<tr>
<td>Italy</td>
<td>0.001</td>
<td>0.480</td>
<td>14033</td>
</tr>
</tbody>
</table>

\( a \) The reported estimates are means over 50 repeats.

\( b \) The reported MAEs evaluate the in-sample fit and are based on the absolute differences between the predicted values and actual values of the entire data which is also used for estimation (e.g. for Finland, the number of observations is equal to 18 [calibration+holdout]; refer to Table 4 for information on other countries).
Table 6
Estimates from GA and NLS when censored datasets are used\(^a\)

<table>
<thead>
<tr>
<th>Country</th>
<th>GA estimates(^b)</th>
<th>NLS estimates</th>
<th>OLS estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(p) (q) (m)</td>
<td>Mean absolute error ((\text{MAE}))</td>
<td>(p) (q) (m)</td>
</tr>
<tr>
<td>Norway</td>
<td>0.005 0.380 1951</td>
<td>225.66</td>
<td>0.005 0.580 1197</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.005 0.390 1650</td>
<td>153.64</td>
<td>0.005 0.460 1136</td>
</tr>
<tr>
<td>Finland</td>
<td>0.0004 0.530 8955</td>
<td>420.21</td>
<td>n.c. n.c. n.c.</td>
</tr>
<tr>
<td>Germany</td>
<td>0.0008 0.480 17 755</td>
<td>357.30</td>
<td>n.c. n.c. n.c.</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>0.002 0.500 20 000</td>
<td>544.96</td>
<td>n.c. n.c. n.c.</td>
</tr>
<tr>
<td>France</td>
<td>0.004 0.460 2164</td>
<td>706.76</td>
<td>n.c. n.c. n.c.</td>
</tr>
<tr>
<td>Italy</td>
<td>0.0003 0.620 17 120</td>
<td>540.31</td>
<td>n.c. n.c. n.c.</td>
</tr>
</tbody>
</table>

\(\text{n.c.}\) = No convergence was achieved.
\(\text{n.p.}\) = RAЕ not possible due to lack of convergence in estimates.
\(^a\) The calibration (in other words, the censored data length) and hold-out periods for each country can be obtained from Table 4.
\(^b\) The reported estimates are means over 50 repeats.
\(^c\) The reported MAEs are based on the absolute differences between the predicted values and actual values of the holdout sample.

The performance of GA with censored datasets is assessed using the Relative Absolute Error (RAE) measure. The RAE between GA, NLS, and OLS are provided in Table 7. The RAE measure indicates that GA performs better than NLS whenever we are able to obtain estimates from NLS with censored datasets. Also, GA is able to provide better forecasts than OLS when censored datasets are used.

In order to obtain a clearer picture regarding which methodology is superior, we use two other measures that are of interest to practicing managers: the peak time period of sales, and sales during the peak of the product life cycle. The time period for peak sales is very critical to product managers because it signifies the end of growth phase and the start of the maturity phase (i.e., when competition increases and profit decreases). Similarly, sales during the peak of a product life cycle indicate the maximum potential a product can achieve under current market/firm conditions. This figure also determines the budget for advertising and other marketing expenditures during the growth phase.
Table 7
Relative absolute error in category sales from various forecasting methods (from censored datasets)

<table>
<thead>
<tr>
<th>Country</th>
<th>NLS(^a)</th>
<th>OLS(^b)</th>
<th>Time series(^c)</th>
<th>Holdout data length(^d)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Norway</td>
<td>0.89</td>
<td>0.93</td>
<td>0.79</td>
<td>9</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.93</td>
<td>0.74</td>
<td>0.92</td>
<td>9</td>
</tr>
<tr>
<td>Finland</td>
<td>N/A</td>
<td>0.73</td>
<td>0.58</td>
<td>11</td>
</tr>
<tr>
<td>Germany</td>
<td>N/A</td>
<td>N/A</td>
<td>0.95</td>
<td>8</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>N/A</td>
<td>N/A</td>
<td>0.4</td>
<td>8</td>
</tr>
<tr>
<td>France</td>
<td>N/A</td>
<td>0.74</td>
<td>0.83</td>
<td>6</td>
</tr>
<tr>
<td>Italy</td>
<td>N/A</td>
<td>N/A</td>
<td>0.76</td>
<td>7</td>
</tr>
</tbody>
</table>

N/A = Not applicable.
\(^a\) RAE of predictions from GA versus predictions from NLS.
\(^b\) RAE of predictions from GA versus predictions from OLS.
\(^c\) RAE of predictions from GA versus predictions from the time series model.
\(^d\) RAE values in this table are based on the holdout data which were not used in the estimation of model parameters.

The time to peak sales for a new product based on the estimates of the Bass model can be obtained from Eq. (4). The predictions of time to peak sales based on estimates from GA, NLS and OLS is provided in Table 8. Based on the results, we see that overall, GA performs better than both NLS and OLS in predicting the time to peak sales of a new product. Also, it can be seen that GA is able to exactly identify the time to peak sales in a majority of the datasets (Finland, Germany, and Italy). Also, the maximum deviation of the predictions based on GA is two time periods (Denmark). It is worth mentioning here that whenever unbiased estimates were obtained from NLS (for Norway and Denmark) the predictions of peak time period from NLS were worse than that provided by GA. In other words, for Norway the prediction based on NLS is off by 6 time periods as compared to 1 time period with the prediction based on GA. Similarly, for Denmark, the prediction based on NLS is off by 3 time periods as compared to 2 time periods for predictions based on GA. The estimates from OLS perform the worst with respect to forecasting the time to peak sales. The predictions based on OLS are off by at least 6 time periods (Denmark) whenever sensible estimates are obtained.

Table 8
Predictions of time (years) to peak sales from various forecasting methods

<table>
<thead>
<tr>
<th>Country</th>
<th>GA</th>
<th>NLS</th>
<th>OLS</th>
<th>Time series</th>
</tr>
</thead>
<tbody>
<tr>
<td>Norway</td>
<td>13 (14)</td>
<td>8 (14)</td>
<td>5 (14)</td>
<td>16 (14)</td>
</tr>
<tr>
<td>Denmark</td>
<td>11 (13)</td>
<td>10 (13)</td>
<td>8 (13)</td>
<td>13 (13)</td>
</tr>
<tr>
<td>Finland</td>
<td>13 (13)</td>
<td>N/A</td>
<td>5 (13)</td>
<td>17 (12)</td>
</tr>
<tr>
<td>Germany</td>
<td>13 (12)</td>
<td>N/A</td>
<td>N/A</td>
<td>12 (12)</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>11 (10)</td>
<td>N/A</td>
<td>N/A</td>
<td>12 (10)</td>
</tr>
<tr>
<td>France</td>
<td>13 (12)</td>
<td>N/A</td>
<td>5 (13)</td>
<td>13 (12)</td>
</tr>
<tr>
<td>Italy</td>
<td>12 (12)</td>
<td>N/A</td>
<td>N/A</td>
<td>13 (12)</td>
</tr>
</tbody>
</table>

N/A = Not applicable.
\(^a\) Value in parenthesis is the actual peak time period in years. The predictions for peak are based on estimates from calibration datasets. The calibration data length for each country is provided in Table 4.
Table 9

Predictions of peak sales (in '000s) from various forecasting methods

<table>
<thead>
<tr>
<th>Country</th>
<th>GA</th>
<th>NLS</th>
<th>OLS</th>
<th>Time series</th>
</tr>
</thead>
<tbody>
<tr>
<td>Norway</td>
<td>359</td>
<td>172.60</td>
<td>157.98</td>
<td>443</td>
</tr>
<tr>
<td>Denmark</td>
<td>306</td>
<td>132</td>
<td>145</td>
<td>337</td>
</tr>
<tr>
<td>Finland</td>
<td>405</td>
<td>N/A</td>
<td>119</td>
<td>484</td>
</tr>
<tr>
<td>Germany</td>
<td>1631</td>
<td>N/A</td>
<td>N/A</td>
<td>1785</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>1717</td>
<td>N/A</td>
<td>N/A</td>
<td>2334</td>
</tr>
<tr>
<td>France</td>
<td>869</td>
<td>N/A</td>
<td>459</td>
<td>995</td>
</tr>
<tr>
<td>Italy</td>
<td>1685</td>
<td>N/A</td>
<td>N/A</td>
<td>1688</td>
</tr>
</tbody>
</table>

N/A = Not applicable.

Value in parenthesis is the actual peak sales. The predictions for peak are based on estimates from calibration datasets. The calibration data length for each country is provided in Table 4.

NLS (for the two datasets where predictions could be obtained) are 226 units (Norway) and 169 units (Denmark). With respect to the estimates from OLS the difference in predictions ranges from 156 units (Denmark) to 411 units (Finland). Also, for each country the predictions based on OLS have the highest difference and the predictions based on GAs have the lowest difference. These results imply that overall a GA estimation technique is a better option for the Bass model during the growth phase of the product life cycle.

5.2. Comparison of results from the Bass model and a time series model

In this section, we compare the forecasting capability of the Bass model against a naive time series model. In order to design a time-series forecasting model for the cellular phone dataset, we plotted the autocorrelations for different lags to determine how to generate a stationary series. All the datasets were stationary with first differences. An examination of the partial auto-correlations revealed that an ARIMA (1,1,0) equation satisfies the sales pattern of a majority of the countries. We hence adopt an ARIMA (1,1,0) equation of the first differences as a naive model for comparison purposes. The time-series equation for each individual country can be represented as:

\[ \Delta y_i = \alpha + \beta_i \Delta y_{i-1} \]  

where \( \Delta y_i \) = first difference of sales of cellular phones in time period \( i \), \( \alpha \) = intercept and \( \beta_i \) = slope parameter. We used one-step ahead forecasts to evaluate the forecasting accuracy from the Bass model using GA and the time series model, when censored datasets are used.

The results are provided in Fig. 5 for a representative country (Finland). To obtain the one-step ahead forecasts, the datasets were re-estimated using GA at every iteration (i.e., as new data points are added). As can be seen from Fig. 5, the one-step ahead forecasts from GA track the actual sales of a new product very closely. The estimates of \( p \) and \( q \), which determine the shape of the distribution, do not change much when new data points are added at each step of the forecasting process. However,
the value of the estimate of $m$ does change when new data points are added. The above pattern is intuitive given that $p$ and $q$ determine the shape of the diffusion curve, and hence need not change with additional information after the inflection point is reached. However, the value of $m$ provides magnitude to the diffusion curve, and the short-term one step ahead forecasts will depend on the value of $m$. It can be inferred from Fig. 5 that GA is very useful to managers to generate short-term one-step ahead forecasts of sales and long-term forecasts regarding the shape of the curve.

The Bass model estimated using GA also fares better than a naïve time series model with respect to one-step ahead forecasts. The RAE for the Bass model versus the time series model is lower (less than one) for all the countries analyzed (as shown in Table 7). However, the maximum deviation based on predictions from GA is two time periods (Denmark) as compared to five time periods (Norway) for predictions from the time series model. Finally, while the naïve time series model performs better than NLS and OLS with respect to predicting the magnitude of peak sales it does not compare well with the Bass model estimated using GA. Specifically, the difference in predicted peak sales and actual peak sales based on the time series model is consistently higher than the respective difference based on the predictions from GA. In summary, the Bass model estimated using GA is clearly the best option when long range forecasting is the requirement. For short-term forecasts, researchers should investigate the utility of a combination of forecasts from the Bass model and a naïve time series model.
Fig. 6. Forecasts for years 2000 and 2001.
5.2.1. Future forecasts

In this section we provide forecasts of future sales of cellular phones (over a two year horizon) in the seven countries studied. The results of this forecasting exercise are provided in Fig. 6. As indicated in Fig. 6a, the sales of cellular phones seem to have stabilized for Finland and Denmark. The prospects for growth are high only for Norway, while the sales of cellular phones are predicted to decline for Germany, UK, Italy, and Denmark. Overall, the telecommunications industry seems to have stabilized and high growth rates as observed in the past may not be experienced in the future. Also, there doesn’t seem to be any drastic changes in the diffusion trend for the future sales. The results of our analyses also imply that the forecasts of sustained growth in the telecommunications industry need to be qualified.

6. Conclusions and future research

In this study we address the issue of forecasting sales in dynamic and turbulent markets such as the telecommunications sector. Specifically during the growth phase, volatility with respect to price, new product offerings and competitor actions, and entry of new brands (as evident in the telecommunication sector) make predicting future sales, time to peak sales and magnitude of peak sales a non-trivial task for product managers. The current slowdown in growth in the telecommunications sector makes such a study of critical importance. In order to achieve this objective we propose a simulation based search technique for estimating the Bass model and illustrate our algorithm by providing predictions of category sales, time of peak sales, and sales at the peak, of cellular phones in seven countries during the growth phase of its life cycle. The results suggest that in the seven European countries in our study the current slowdown in growth in the wireless phones market is a long-term phenomenon. The forecasts based on GA suggest that the sales of cellular phones are (1) expected to grow only in Norway, (2) the sales have reached a stationary state in Finland and Denmark, and (3) the sales is expected to slowdown in France, UK, Italy, and Germany. The results indicate that overall the growth rate for cellular phones is reaching maturity and that firms should focus on newer and useful innovations if they need to sustain their current growth rate and profit margins.

The forecast of wireless subscribers in our study was accomplished by estimating the Srinivasan and Mason (1986) operationalization of the Bass diffusion model using GA. The results from our analyses using GA are very encouraging to both practitioners and researchers alike. It is found that the predictions from GA are robust across many datasets and are better than OLS and NLS with respect to both Relative Absolute Error (RAE) and predictions of time to peak sales, when forecasting is done in the growth phase and the maturity phase of product life cycle. The Bass model estimated using GA also performed better than a naïve time series model (Eq. (7)). The estimates generated from a GA also have desirable properties such as (1) a normal distribution and (2) bounded variance.

Future research studies can investigate the utility of including several exogenous factors such as price, competitive intensity, and network effects in obtaining better predictions during the growth phase. The recent phase of consolidation in the telecommunications industry could provide avenues to investigate how the competitive intensity, measured in terms of market share concentration or price volatility, influences the diffusion of new products and telecommunications equipment in particular. Also, the telecommunication industry is dependent to a large extent on network externalities such as high bandwidth for better communication facilities and hence higher rates and levels
of adoption. The above examples illustrate some representative theoretical and managerial issues that need to be resolved in the telecommunications sector related to product/service adoption. The technique proposed in this study can be used as a basis for further investigation of product adoption in nascent markets. Researchers should also investigate the applicability of these results across different product categories, especially those that have different product market characteristics such as High Definition Televisions. In this study, we investigate only one aspect of the drawbacks in using NLS for estimating the Bass model. The issue of systematic change and bias in parameter estimates of the Bass model when using NLS still needs to be investigated. GAs could very well serve as an alternative estimation technique under this scenario.

Of primary interest however, would be to investigate the performance of GAs compared to newer techniques such as Hierarchical Bayes, Kalman filtering, and any combinations of these methods. Also, research is needed on deriving algorithms to combine the forecasts from these different techniques.

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References


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