

27th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM2017,  
27-30 June 2017, Modena, Italy

# Applying Looks-Like Analysis and Bass Diffusion Model Techniques to Forecast a Neurostimulator Device with No Historical Data

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## Abstract

This work utilizes looks-like analysis and the Bass diffusion model to generate sales forecasts of a responsive neurostimulation (RNS) system. Due to the lack of historical data, a combination of techniques is utilized to predict the device's demand. Looks-like analysis is used to analyse analogous devices and their sales patterns to select the device closest to the RNS system. Next, parameters for the Bass diffusion model are estimated, and potential baseline forecasts are developed using two methods. Results suggest that peak sales for the device will occur around years 2021-2024.

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Peer-review under responsibility of the scientific committee of the 27th International Conference on Flexible Automation and Intelligent Manufacturing

**Keywords:** Bass Diffusion Model; New Product Forecasting; Demand Forecasting; Coefficient of innovation; Coefficient of imitation

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## 1. Introduction

For many organizations, factors such as time to market, strategic planning, productivity, and customer satisfaction are critical for an organization's survival. Moreover, new product offerings are essential for maintaining a successful business and competitive edge against competitors. As a consequence, making decisions concerning resource allocation to new product development and launch continues to be an important responsibility for strategic

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planning. To determine potential supply and demand for new products, organizations utilize forecasting techniques. Assessing the impact and adoption of the new product and predicting the development of new markets are crucial aspects of the forecaster's responsibility.

The assumptions forecasters make are typically based on the fact that future sales patterns will, by and large, imitate the past. Therefore, simple extrapolation techniques like those mentioned by Kaes and Azeem [1] and Laplan and Whisler [2] may well suffice. However, in the case of new products, forecasters may struggle to develop realistic forecasts in an environment where past data and adequate market research is scarce. Despite challenges facing new product forecasting, a structured data gathering approach combined with proven forecasting models can be applied to new products to provide invaluable insight into long run market acceptance.

This paper focuses on a to-be-launched responsive neurostimulation (RNS) device by Neuropace, which is being investigated to treat epilepsy. Since the RNS system is the first of its kind, there is little to no historical data that will permit the use of traditional forecasting extrapolation. Thus, the objective of this paper is to generate a baseline market demand forecast for the RNS system using looks-like analysis (based on forecast analysis of an analogous product with similar features and functions) combined with Bass diffusion models. The Bass diffusion models are used to determine the number of sales at a certain time based on parameters like the coefficient of innovation ( $p$ ) and the coefficient of imitation ( $q$ ).

In this report, two methods of determining  $p$  and  $q$  to generate potential baseline forecasts are discussed. The three methods are as follows:

1. Calculate  $p$  and  $q$  from an analogous product's past sales
2. Calculate  $p$  and  $q$  from various analogous products whose  $p$  and  $q$  estimates are provided.

The  $p$  and  $q$  values for each of two methods are then inputted into the Bass diffusion model to develop potential baseline forecasts.

This paper is organized as follows. In Section 2, prior literature regarding applications of new product forecasting, looks-like analysis, and Bass diffusion models is discussed. In Section 3, we provide a general overview of the Bass diffusion model. Sections 4 and 5 discuss the selection process and sales pattern of an analogous product whose sales data is provided, and Sections 6 and 7 discuss the two methods of calculating  $p$  and  $q$ . Section 8 provides the forecasts using the two methods, and Section 9 provides a discussion and summary of the work.

## 2. Literature Review

New product forecasting has been discussed in literature as it has become necessary for certain industries to invest in new products. Simon [3] asserts this claim and expands on the important factors of new product development, and Jahanbin et al. [4] specifically looked at the mobile phone industry and discussed the importance of new product forecasting in order to meet changes in technological advancements and global competition. Furthermore, it has been discussed that new product forecasting is different from regular sales forecasting since new product forecasting varies as the product moves from early stages to the launch stage of new product development (NPD). Khanh [5] lists how new product forecasting changes during different development stages like the strategic planning, concept generation, pre-technical evaluation, technical development, commercialization, and post-launch stages.

Related work on looks-like analysis have also been reviewed for the purposes of this study. Kahn [6] conducted an exploratory investigation of new product forecasting practices and determined that looks-like analysis was used 30 percent of the time among all the forecasting techniques available to companies. When discussing the key aspects of looks-like analysis, Lilian and Rangaswamy [7] assert that the critical component of looks-like analysis is that the product and its historical data should reflect a similar level of innovation and time-to-market of the new product in question.

Moreover, the Bass diffusion model has been applied to various forecasting situations. Some applications include those outlined in [8], [9], [10], and [11]. In the next section, we provide an overview of the Bass diffusion model, including its assumptions and general formulae. We then apply both looks-like analysis and two Bass diffusion models to the RNS system in the sections that follow.

### 3. Overview of Bass Diffusion Model

The Bass diffusion model, first discussed in [12], focuses on the growth (adoption) and spread (diffusion) of new products. It offers a good baseline forecast of long-term sales patterns of new products and technologies under two conditions: (1) the firm has recently launched the product and has few periods of historical sales data available, and (2) the firm has not yet produced the product, but it is similar in some way to existing products whose sales history is known.

Under the Bass diffusion model, buyers are separated into two groups: innovators and imitators. Innovators are buyers who are more receptive to new products and are the first to buy them, while imitators are buyers who purchase a new product based on influence and interaction with others who have already adopted the new product in question. Fig. 1 shows how the number of adopters for innovators and imitators changes over time.

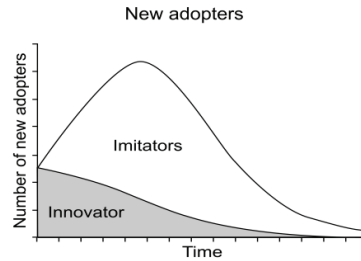


Fig. 1. Number of adopters versus time

The mathematical model, known as the Bass Model Principle, is presented in Equation (1). The model allows the forecaster to determine the probability of a purchase at time  $t$  given that the individual has not previously purchased the product.

$$n(t) = p(0) + \frac{q}{m} N(t) \quad (1)$$

Where  $n(t)$  = probability of purchase at time  $t$   
 $p(0)$  = coefficient of innovation at time  $t = 0$   
 $q$  = coefficient of imitation  
 $m$  = total number of buyers in the market  
 $N(t)$  = number of people who have adopted the product at time  $t$

Of interest are the coefficients  $p$  and  $q$ . The coefficient  $p$ , also known as the coefficient of innovation, reflects the adopters who accept the product without social influence, while the coefficient  $q$ , known as the coefficient of imitation, reflects the adopters who try the product due to social influence.

Over the years, the Bass Model Principle has been extended in order to model different situations. If treated as a continuous density function over time, the Bass Model Principle is represented as shown in Equation (2).

$$n(t) = pm + (q - p)N(t) - \frac{q}{m} (N(t))^2 \quad (2)$$

Where  $n(t)$  = Sales in period  $t$   
 $N(t)$  = Cumulative sales to period  $t$   
 $m$  = Total number of buyers in the market  
 $p$  = Coefficient of innovation  
 $q$  = Coefficient of imitation

Equation (2) can also be made discrete by replacing continuous time  $t$  with discrete periods of time, where  $t$  is the current period and  $t+1$  is the next period. This discrete form is presented in Equation (3). The values for  $m$ ,  $p$ , and  $q$  can be calculated using Equations (4) through (6), respectively, and the parameters  $a$ ,  $b$ , and  $c$  can be estimated using least squares regression.

$$n(t) = a + bN(t-1) - c(N(t-1))^2 \quad (3)$$

$$m = \frac{-b - \sqrt{b^2 - 4ac}}{2c} \quad (4)$$

$$p = \frac{a}{m} \quad (5)$$

$$q = p + b \quad (6)$$

In addition to the continuous and discrete forms of the model, a generalized Bass model was established by Bass, Krishnan, and Jain [13]. This form of the model incorporates the effects of marketing-mix variables on the likelihood of adoption and allows  $m$ ,  $p$  and  $q$  to vary over time. Because the original Bass model has been well-established, however, we will use the original model in our calculations.

#### 4. Selection of an Analogous Product

Our first step in determining a baseline forecast is to determine an analogous product whose past sales data is already provided. We do this by searching through other literature for products that already exist in the market and comparing their features and functions to those of the new RNS system. Two brain stimulation devices – Cyberonics VNS System and Medtronic Activa PC – were found and were compared to the RNS System [14]. Table 1 compares factors including FDA regulations, barriers to entry, symptoms treated, and various functions and features for each of the three devices. A cell with a dot (•) signifies that the particular product has that factor. From Table 1, we can see that the Cyberonics VNS System has the closer score and is thus considered the analogous product.

#### 5. Data Collection of VNS System

Data on the VNS System was gathered by reviewing the Cyberonics, Inc. annual 10K reports from 1998-2011 [15]. The data consisted of total VNS units sold in the United States for a given year, the average price per unit, and sales revenue. These inputs were then used to calculate the cumulative sales and the percent change in average price per unit. The sales data for the VNS System is provided in Table 2.

#### 6. Method #1: Calculate $p$ and $q$ from an analogous product's (VNS System's) past sales

In order to calculate  $p$  and  $q$ , a regression line of the cumulative sales and sales per year of the analogous VNS System was determined. Data from Table 2 was inputted into Minitab, and the spreadsheet generated the quadratic nonlinear regression line listed in Equation (7). Fig. 2 shows the regression line plotted with the VNS System cumulative sales.

$$S = 3495 + 0.1153C - 0.000001C^2 \quad (7)$$

where  $S$  is the sales per year, and  $C$  is the cumulative sales per year.

It is evident that Equation (7) follows the same format as the discrete Bass diffusion model in Equation (3). Thus, from Equation (7), the coefficient  $a = 3495$ , the coefficient  $b = 0.1153$ , and the coefficient  $c = -0.000001$ . Knowing these coefficients, we can then use Equations (4), (5), and (6) to estimate the parameters  $m$ ,  $p$ , and  $q$ , respectively. The results are listed below in Table 3.

It should be noted that the calculated value of  $m$  is 140,224 but was rounded to 140,000 to further simplify our calculations. Additionally, the estimate of  $m$  was used for all three methods of estimating  $p$  and  $q$  since it was assumed that the market size would be consistent regardless of which method was used.

The parameters were then inserted into the Decision Pro software, and potential baseline forecasts were generated using the Bass diffusion model. These are shown in Section 8.

Table 1. Comparison of Neuropace RNS System, Cyberonics VNS System, and Metronic Activa PC

| Neuromodulator Device  |                      | VNS System | Activa PC | RNS System | Factor weight |
|------------------------|----------------------|------------|-----------|------------|---------------|
| FDA                    | Regulated            | •          | •         | •          | 4             |
|                        | Approved             | •          |           |            | 5             |
| Barrier to entry       | Low                  | •          | •         | •          | 3             |
|                        | High                 |            |           |            | 4             |
| Symptoms treated       | Partial Epilepsy     | •          |           | •          | 5             |
|                        | Depression           | •          |           | •          | 4             |
|                        | Essential tremors    |            | •         |            | 3             |
|                        | Parkinson disease    |            | •         |            | 3             |
| Implantable components | Pulse generator      | •          | •         | •          | 5             |
|                        | Depth leads          |            |           | •          | 5             |
|                        | Cortical strip leads |            |           | •          | 5             |
|                        | Bipolar leads        | •          |           |            | 4             |
| External components    | Programmer           | •          | •         | •          | 5             |
|                        | Laptop               | •          | •         | •          | 5             |
|                        | Software             | •          | •         | •          | 5             |
|                        | Wand                 | •          | •         |            | 5             |
|                        | Telemetry Interface  | •          | •         | •          | 5             |
| Battery type           | Primary              | •          | •         | •          | 5             |
| Technology             | Open loop            | •          | •         |            | 3             |
|                        | Close loop           |            |           | •          | 4             |
| TOTAL SCORE            |                      | 62         | 50        | 64         |               |

Table 2. VNS System sales per year and revenues from 1998-2011 for the U.S. market

| Year      | Sales per year | Cumulative sales | Average price per unit (\$) | % change average price per unit | Sales revenue (\$ millions) |
|-----------|----------------|------------------|-----------------------------|---------------------------------|-----------------------------|
| 1998-1999 | 2711           | 2711             | 9700                        | 1                               | 26.3                        |
| 1999-2000 | 3556           | 6267             | 11950                       | 1.188284519                     | 42.5                        |
| 2000-2001 | 3893           | 10160            | 12251                       | 1.2082279                       | 47.7                        |
| 2001-2002 | 4400           | 14930            | 14500                       | 1.331034483                     | 63.8                        |
| 2002-2003 | 6600           | 22085            | 14500                       | 1.331034483                     | 95.7                        |
| 2003-2004 | 6925           | 28712            | 14150                       | 1.314487633                     | 98                          |
| 2004-2005 | 5680           | 35093            | 15900                       | 1.389937107                     | 90.3                        |
| 2005-2006 | 6792           | 41885            | 17000                       | 1.429411765                     | 108                         |
| 2006-2007 | 6693           | 48578            | 17000                       | 1.429411765                     | 111.1                       |
| 2007-2008 | 4495           | 54642            | 21000                       | 1.538095238                     | 94.5                        |
| 2008-2009 | 6613           | 61255            | 17374                       | 1.441694486                     | 114.9                       |
| 2009-2010 | 7069           | 68324            | 19000                       | 1.489473684                     | 135.1                       |
| 2010-2011 | 7906           | 76230            | 21000                       | 1.538095238                     | 161.2                       |

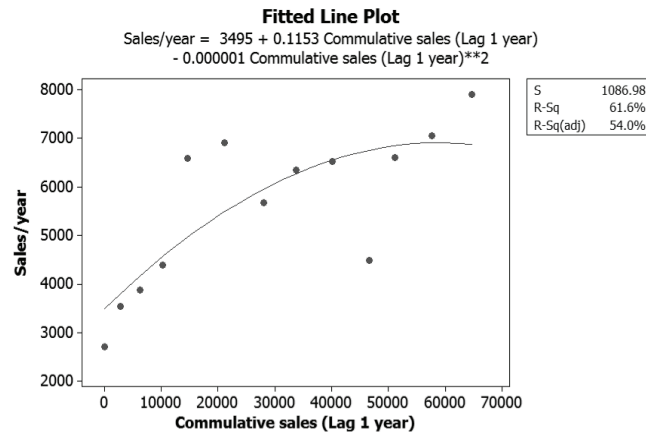


Fig. 2. Fitted line plot for VNS System

Table 3. Estimations of  $p$ ,  $q$ , and  $m$ 

| Parameter                       | Value   |
|---------------------------------|---------|
| $m$ (Market size)               | 140,000 |
| $p$ (Coefficient of innovation) | 0.02496 |
| $q$ (Coefficient of imitation)  | 0.14026 |

Table 4. Values of  $p$  and  $q$  for Silver Medical neuro-monitoring device

| Silver Medical device | $p$           | $q$           |
|-----------------------|---------------|---------------|
| In sepsis population  | 0.0052        | 0.8328        |
| In brain injury       | 0.0051        | 0.861         |
| In stroke population  | 0.0041        | 0.7062        |
| <b>Average</b>        | <b>0.0048</b> | <b>0.7817</b> |

## 7. Method #2: Calculate $p$ and $q$ from analogous products whose $p$ and $q$ estimates are provided.

For the second method, three different medical devices whose functions and features were similar to the RNS system were identified. These devices had calculated  $p$  and  $q$  values, and were therefore relevant to our analysis. Table 5 lists the three devices, and their  $p$  and  $q$  values. A weighted average of the  $p$  and  $q$  values of these devices are used to provide the  $p$  and  $q$  estimates of our device. The weights are assigned based on proximity to the analysis time period of our device, which was granted FDA approval in 2013 [16]. The analysis period for the CT scanners (>100 beds) device is closest to the period for our device, and is hence given a higher weight.

Table 5. Weighted average estimations of  $p$  and  $q$ 

| Medical device          | Analysis period | Weight | $p$          | $q$          |
|-------------------------|-----------------|--------|--------------|--------------|
| Ultrasound imaging      | 1965-1977       | 1      | 0.001        | 0.51         |
| Mammography             | 1965-1976       | 1      | 0.000        | 0.738        |
| CT scanners (>100 beds) | 1974-1985       | 2      | 0.034        | 0.254        |
| <b>Weighted average</b> |                 |        | <b>0.017</b> | <b>0.439</b> |

## 8. Producing the sales forecasts of the RNS system

The  $p$  and  $q$  values computed from methods 1 and 2, along with the Bass diffusion model are used to produce forecasts for the RNS system device through the year 2040. Table 6 shows the sales forecasts for each method. Fig. 3 plots the sales-per-year forecasts, and Fig. 4 plots the cumulative sales forecasts. While the forecasts from methods 1 and 2 differ, the forecasts overall suggest that peak sales would occur around the years 2021-2024.

Table 6. Potential baseline forecasts for sales per year and cumulative sales

| Method                           | Method 1       |                  | Method 2       |                  |
|----------------------------------|----------------|------------------|----------------|------------------|
|                                  | Sales per year | Cumulative sales | Sales per year | Cumulative sales |
| <b>Total market potential, m</b> | 140,000        | 140,000          | 140,000        | 140,000          |
| <b>Parameter p</b>               | 0.025          | 0.025            | 0.017          | 0.017            |
| <b>Parameter q</b>               | 0.140          | 0.140            | 0.439          | 0.439            |
| <b>2013</b>                      | 3,500          | 3,500            | 2,380          | 2,380            |
| <b>2014</b>                      | 3,890          | 7,390            | 3,367          | 5,747            |
| <b>2015</b>                      | 4,295          | 11,686           | 4,702          | 10,448           |
| <b>2016</b>                      | 4,707          | 16,393           | 6,447          | 16,895           |
| <b>2017</b>                      | 5,116          | 21,509           | 8,615          | 25,510           |
| <b>2018</b>                      | 5,511          | 27,020           | 11,104         | 36,614           |
| <b>2019</b>                      | 5,877          | 32,897           | 13,627         | 50,241           |
| <b>2020</b>                      | 6,201          | 39,098           | 15,667         | 65,908           |
| <b>2021</b>                      | 6,468          | 45,566           | 16,572         | 82,480           |
| <b>2022</b>                      | 6,664          | 52,230           | 15,854         | 98,335           |
| <b>2023</b>                      | 6,778          | 59,008           | 13,556         | 111,890          |
| <b>2024</b>                      | 6,804          | 65,812           | 10,340         | 122,231          |
| <b>2025</b>                      | 6,737          | 72,549           | 7,113          | 129,343          |
| <b>2026</b>                      | 6,580          | 79,129           | 4,503          | 133,847          |
| <b>2027</b>                      | 6,338          | 85,468           | 2,687          | 136,534          |
| <b>2028</b>                      | 6,024          | 91,492           | 1,543          | 138,077          |
| <b>2029</b>                      | 5,651          | 97,142           | 865            | 138,942          |
| <b>2030</b>                      | 5,235          | 102,377          | 479            | 139,421          |
| <b>2031</b>                      | 4,792          | 107,169          | 263            | 139,684          |
| <b>2032</b>                      | 4,339          | 111,509          | 144            | 139,828          |
| <b>2033</b>                      | 3,889          | 115,398          | 78             | 139,906          |
| <b>2034</b>                      | 3,454          | 118,852          | 43             | 139,949          |
| <b>2035</b>                      | 3,042          | 121,894          | 23             | 139,972          |
| <b>2036</b>                      | 2,660          | 124,554          | 13             | 139,985          |
| <b>2037</b>                      | 2,310          | 126,864          | 7              | 139,992          |
| <b>2038</b>                      | 1,995          | 128,859          | 4              | 139,996          |
| <b>2039</b>                      | 1,714          | 130,573          | 2              | 139,998          |
| <b>2040</b>                      | 1,467          | 132,040          | 1              | 139,999          |

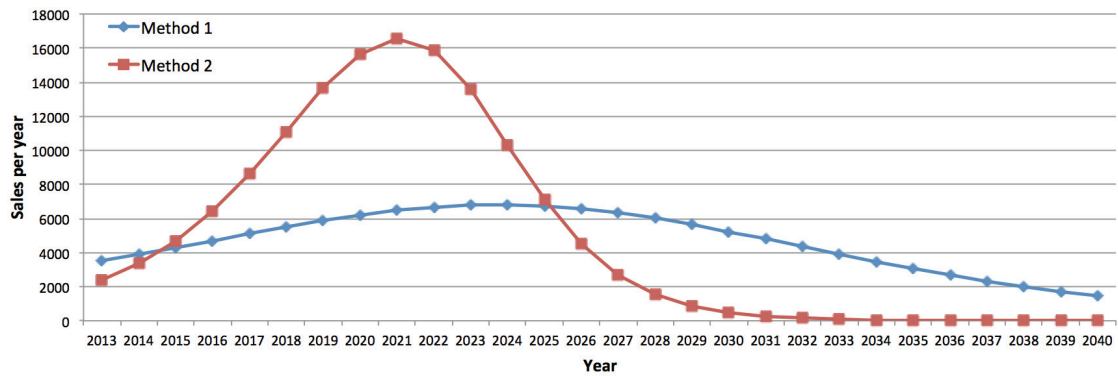


Fig. 3. Sales per year forecasts using the 2 methods

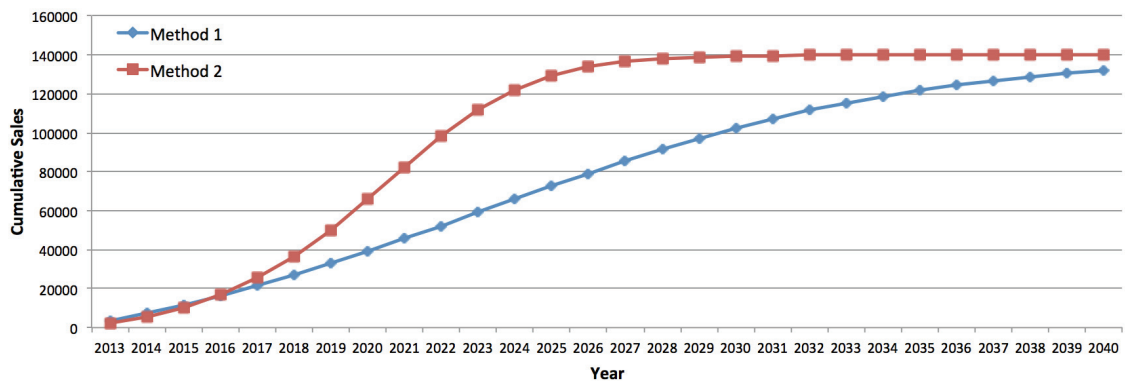


Fig. 4. Cumulative sales forecasts using the 2 methods

## 9. Conclusion

The goal of this work was to provide Neuropace with sales forecasts of their new RNS System. Using looks-like analysis and Bass diffusion models, we developed demand forecasts for the RNS System using two different estimation methods to compute the coefficient of innovation ( $p$ ) and the coefficient of imitation ( $q$ ). These values were inputted into the Bass diffusion model. The sales per year and cumulative sales forecasts were produced, which suggest peak sales around years 2021-2024. Knowing when the peak sales occur would assist in the supply chain management of the production of the new device.



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