

Life Cycle Prediction: A Comparison of Methods for a Lighting Products Retailer

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Abstract

Product life cycle (PLC) prediction is one of the most challenging yet critically important aspects of supply chain management. Lost sales and excess inventory costs arise when there is a mismatch between demand and supply, especially at the beginning of a product's life cycle when a new product is launched. Our proposed framework contributes to the application of decision-support systems in the prediction of PLCs of new products. In this study, we fit piecewise-linear curves, n -th order polynomial curves, and Bass diffusion curves for PLC prediction and compare their effectiveness using real data from a retailer specializing in lighting products. We estimate the PLCs of 2,615 lighting products using these models and select the best-fit curve to predict their PLCs. We also develop an algorithm to address challenges posed by imbalanced datasets and apply it in neural networks for predictive modeling to determine a product's PLC stage, demand class, and stocking decisions. The findings show that fourth-order polynomial curves can accurately predict the PLCs of 63% of the products. Bass diffusion curves emerge as the second-best performer. Our approach can be generalized to other products in other industries, and it can effectively guide end-of-life inventory decisions.

Managerial Relevance Statement

Accurate life-cycle prediction holds vital significance for both manufacturers and retailers, guiding their inventory and sales strategies. Manufacturers must align production schedules and shipments with sales forecasts prior to new-product launches. Similarly, retailers are tasked with determining order quantities and optimal inventory allocation to meet customer demands efficiently. Managers can plan for production, inventory, staffing, and marketing based on projected demand at different stages of a product's life cycle. This prevents over- or under-investment in resources, optimizing operational efficiency. Similarly, understanding the product's life cycle helps managers determine when to invest in research and development for new features, improvements, or entirely new products. Early-stage investment might be necessary to sustain the growth phase, while late-stage investment could focus on extending the product's decline phase. Also, the product life cycle plays a pivotal role in strategic warranty management by integrating technical and commercial considerations from product conception

to obsolescence. Manufacturers can share necessary information based on the life-cycle prediction of products with retailers in advance, to plan accordingly for new products and sales.

Keywords: Product Life Cycle Prediction; Inventory Management; Bass Diffusion Model; Piecewise Linear Curves; Polynomial Curves; Neural Networks

1 Introduction

Companies introduce new products to compete and grow. In today’s dynamic and competitive business landscape, efficient inventory management stands as a cornerstone of organizational success [1]. As companies strive to optimize their operational efficiency while meeting customer demands, accurate predictions of the demand and the product life cycle (PLC) become increasingly crucial for business success [2]. This applies not only to physical products but also to digital products, such as software [3]. Both physical and digital products go through a beginning-of-life, middle-of-life, and end-of-life phase, and the challenge lies in predicting when a product transitions from one phase to another. Systematically managing PLC phases for each product facilitates the seamless integration of product-related information [4] and positively impacts new product development efforts as well as life cycle management across a portfolio of products.

Unlike a single static prediction, a PLC curve projection captures sales trends across different stages of a product’s life cycle, from introduction and growth to maturity and decline [5]. The ability to forecast demand and product life cycles enables businesses to make informed decisions about procurement, production, and distribution, optimizing operational efficiency [6].

This proactive approach not only ensures product availability during periods of high demand but also helps prevent overstocking and waste as interest declines [7]. In this context, integrating PLC prediction with inventory management is essential for manufacturers and retailers to meet customer needs, reduce operational costs, and enhance overall profitability [8].

The PLC prediction has become increasingly important in the era of “big data,” where firms accumulate huge amounts of information and base decisions on massive datasets. As a result, conventional decision-support tools are becoming less effective [9]. In this rapidly evolving environment, leveraging artificial intelligence (AI) through data mining and analytics is essential for navigating market uncertainty and identifying emerging opportunities [10].

Among AI techniques, artificial neural networks are the most widely used in supply chain and operations management, as they can uncover complex patterns that may go unnoticed by humans [11]. Companies collect extensive product data across all life stages, and AI enables precise forecasting and deep insights by analyzing massive datasets. This approach supports well-informed decision-making based on real-time and historical data, rather than relying solely on intuition or past managerial experience. Most importantly, AI-driven decision-support systems can be con-

tinuously updated, even daily, based on new data, allowing management to adapt to market dynamics and respond to changes more effectively.

This study is driven by a real industry problem, using actual market demand data to address key challenges in inventory management and demand prediction. These issues were raised by a major retailer of lighting products in the UK. The lighting retailer offers products for residential, commercial, and industrial applications. They suffered from poor inventory decisions along the life cycle of the products they offer to the market and sought an approach that could improve their inventory stocking decisions through the application of the product life cycle management concept. Our literature review identified existing works around factors affecting stocking decisions, product life cycle characteristics, and the process of making stocking decisions. While the retailer recognized the importance of individual life cycle stages, no overarching product life cycle approach was currently in use. Their decision-making process was reactive to changes in the market and solely based on the demand volume, rather than on other products in the portfolio or new products that would be introduced into the portfolio. While the retailer wanted to satisfy the demand in the market, they also wanted to become leaner in inventory to reduce warehousing costs and capital tied up in stocks.

We received order data for thousands of products, both active and inactive, as the database had never been cleaned to remove discontinued products. Additionally, we collected qualitative data to capture insights not reflected in the database. This effort aimed to understand decision-making processes related to new product introductions, inventory management, and discontinuation strategies when products reach the end of their life cycle.

To gain deeper insights, we conducted informal conversations with experts directly involved in stocking decisions, as well as professionals with extensive experience in supply chain, inventory, and product management in the company. Our findings revealed that many management challenges arise from a lack of understanding of a product’s life cycle and its stages. To improve life cycle predictions and enhance operational decision-making, we propose using PLC curves methods and advanced AI methods commonly used in operations management, such as clustering and artificial neural networks.

Our approach focuses on predicting demand for new products by analyzing historical demand patterns and fitting them into PLC curves. This allows us to estimate demand at different PLC stages—introduction, growth, maturity, and decline—and compare the effectiveness of various PLC prediction models using historical data from the retailer. These comparisons inform inventory decisions at each PLC stage, improving overall inventory management.

To achieve this, our framework includes data preparation, PLC curve fitting, product clustering based on functionality, PLC estimation for new products, and neural network modeling. Using a combination of these techniques helps identify the most effective approach for guiding operational decisions, such as inventory planning. Ultimately, we highlight the importance of automated decision-support systems that can adaptively select the appropriate method based on market response.

Unlike a single fixed prediction, a PLC curve forecast captures sales patterns across a product’s life cycle, from introduction to growth [5]. This research aims to develop an accurate PLC curve forecast before a product’s launch in a retail environment. By doing so, we provide essential insights to manage the product’s launch and growth stages, offering a more comprehensive understanding of its expected performance over time. Our research makes the following contributions:

- Our proposed framework contributes to the application of AI-enhanced decision-support systems for PLC prediction of new products.
- We identify the most suitable PLC curve for existing products by clustering them based on functionality. When a new product is launched, its PLC is predicted using the PLCs of similar existing products.
- By analyzing data and PLC curves, we gain deeper insights into market behavior, equipping management with valuable information for demand forecasting and improved operations management.
- We develop an algorithm to address challenges posed by imbalanced datasets and integrate it into predictive modeling using neural networks.

At first glance, accurate PLC predictions for new products may seem relevant only to inventory management and logistics operations. However, we explore how they impact broader strategic decisions beyond inventory management. Precise PLC estimation enables management to develop resilience plans for operations and supply chain networks. We also provide managerial insights from this perspective.

The subsequent sections of the paper start with our Literature Review section. Then, our Methodology section describes our data cleaning and preparation, explains our PLC curve fitting methodology, and presents our PLC forecasting method for new products. The Findings section presents and discusses the results. We conclude with a section on the study’s conclusions, managerial implications, research limitations, and suggestions for future research.

2 Literature Review

Our work is related to two main streams of literature: PLC forecasting and new product demand forecasting. Both streams utilize data-driven and AI methodologies to address operational management challenges. PLC theory provides a comprehensive description of the stages of a product: introduction, growth, maturity, and decline. PLC curve modeling is a fundamental but still challenging issue from both theoretical and practical perspectives. Classical PLC curve theory relies on the Bass diffusion model and its various adaptations [12]. Over time, it has been modified in multiple ways, including changes to its mathematical formulation and operational implementation [13, 14]. For example, a stochastic Bass model can be developed, allowing parameters to vary across periods [15].

2.1 PLC curve modeling and forecasting

There are two main categories of PLC forecasting methods: Curve fitting methods and AI-based techniques. Several studies have explored alternatives to the Bass PLC curve for historical PLC prediction, with two commonly used approaches being the polynomial PLC curve and the piecewise linear PLC curve [16]. The polynomial PLC curve has been validated in the service industry, including the study on the Mississippi casino industry [17]. The piecewise linear PLC curve has been found to apply to 23.3% of 258 ethical drug products [18]. Additionally, both the polynomial PLC curve and the piecewise linear PLC curve have been successfully applied to Dell’s product data, reinforcing their effectiveness across different contexts [2].

More recently, Bayesian functional regression has been proposed as an alternative approach for forecasting the PLC of new products. [5] introduced a Bayesian functional regression framework to model and forecast the PLC curves of new consumer products using data from JD.com. Building on this, [19] developed a Bayesian ensemble model that leverages completed life cycles of comparable products to predict the PLC of new products. Their framework is validated using demand data from 86 Intel microprocessors. While both studies present important methodological advancements, particularly in ensemble forecasting, they focus primarily on improving statistical accuracy through model-based extrapolation. Specifically, the framework in [19] does not incorporate clustering or the use of product attributes to identify similar products. Moreover, neither study integrates AI techniques for broader decision-support applications such as demand classification, PLC stage prediction, or inventory planning. Additionally, their models are not benchmarks against traditional PLC curve-fitting methods, limiting comparative insight into model performance.

The second category of PLC forecasting for new products is AI-based methods. Forecasting PLC for a new product poses a challenge in the fields of operations management and marketing due to the scarcity or absence of historical data. Additionally, it requires the analysis of complex relationships among various market variables. Therefore, the role of AI techniques in overcoming this problem has become more prominent.

AI-based models, utilizing machine learning and deep learning techniques, simulate the diffusion patterns of new products based on the characteristics of existing ones. The AI-based PLC forecasting model developed by [20] uses a hidden influence network to predict the PLC of new products. [21] proposed a data-mining approach for PLC prediction in e-commerce platforms. Both [2] and [22] employed clustering techniques to forecast the PLC of new products. [23] conducted a comparative analysis of life cycle prediction models for existing products, including Bass diffusion, piecewise linear, and polynomial curves, using sales data from a lighting products retailer. While their work offers valuable insights into model performance for PLC estimation, it focuses primarily on curve-fitting accuracy and does not address forecasting the PLC or demand for new products, nor does it integrate AI-based classification methods or demand-type forecasting.

In this paper, we propose a data-driven framework grounded in practice that integrates the Bass diffusion model, curve-fitting models, and AI techniques to predict the PLC curve of new products before their launch. By leveraging historical data, these approaches enhance decision-making [11, 24].

2.2 New product demand forecasting

Demand forecasting, particularly for new products, plays a crucial role in marketing and operations management. Demand forecasting is one of the four key stages in the new product development process [25]. Research on forecasting demand for new products has been a focus in operations management and marketing for several decades [25]. Broadly, demand forecasting methods fall into two main categories: diffusion models and AI-based techniques.

One of the primary models for forecasting demand is the Bass diffusion model [26, 5], which predicts the lifetime demand of a new product based on three key parameters: market size, external influence, and internal influence [12, 27]. Over the past two decades, significant modifications have been made to the original Bass model [13, 14, 28]. For example, Bass [29] explored critical extensions, focusing on how successive generations of products diffuse and how contextual factors such as pricing can be incorporated into the model. [30] further enhanced the Bass model by integrating social data and consumer recommendations. Despite these advancements, the Bass model may produce significant prediction errors when forecasting demand for new products before their launch due to the lack of historical data [31].

The second category of demand forecasting for new products is AI-based methods. With advancements in technology, companies collect vast amounts of digital data, enabling the use of data-driven tools to enhance demand forecasting accuracy. AI-based forecasting methods have emerged as a powerful alternative to traditional models [24, 26]. For instance, [24] applied a data-driven approach and machine learning algorithms to forecast demand for short-life cycle products with non-stationary demand. [32] combined fuzzy clustering techniques with ensemble deep learning to improve new product demand forecasting. [33] employed artificial neural networks, support vector machines, and regression methods to predict demand for spare parts in construction machinery, demonstrating that artificial neural networks and support vector machines outperform regression methods. [34] integrated domain knowledge with neural networks to improve demand predictions for new products. [31] applied both traditional statistical models and deep neural networks to forecast demand for short-life cycle products. [35] proposed a data-driven framework that combines homogeneity-based clustering with machine learning techniques to forecast demand for new products with short life cycles in the smartphone market. The primary objective of their study is to improve forecasting accuracy by addressing the limitations of traditional attribute-based methods.

Previous studies predominantly utilize either PLC curve fitting or AI techniques independently, focusing solely on PLC forecasting. This limitation leaves a gap in providing broader, high-level insights necessary for effective decision-

making in new product management. Our study addresses this gap by introducing a comprehensive framework that uniquely integrates both PLC curve fitting to predict sales volumes of new products and advanced AI techniques, such as neural networks, to predict the demand class, product life cycle stage, and stocking decision. Unlike most prior research that relies on a single approach, our model offers a dual advantage: it not only provides precise forecasting of the sales volume along a new product’s life cycle, but it also generates high-level insights by predicting three critical features for new products—demand classification, specific PLC stage, and stock decision. This integrated approach empowers operations managers to accurately categorize products based on expected demand, assess the product’s position within the PLC, and make well-informed inventory decisions, ultimately enhancing both strategic planning and operational efficiency by leveraging all products in the product portfolio.

To achieve these improvements, we apply various AI techniques to enhance PLC prediction. We use data mining for preprocessing and clustering techniques to group products based on similarity, facilitating more accurate PLC forecasting. To assess the accuracy of our predictions, we employ an out-of-sample methodology. Additionally, we use artificial neural networks to classify demand for new products. Methodologically, our work is most closely related to [2], which integrates curve-fitting methods and clustering to improve PLC forecasting for new products. However, our framework extends beyond their approach by incorporating AI-driven demand classification and stock decision-making insights, making it a more holistic and actionable tool for operations managers.

To further clarify how our study advances the literature, we provide a summary table (Table 1) that compares existing work in terms of methodology, dataset, and limitations. As shown in the table, previous studies often rely on either curve-fitting models or machine learning techniques. While a few previous studies have addressed PLC and demand forecasting for new products, such as [2] and [24], these efforts are limited either in scope, modelling depth, or integration of advanced decision-support features.

What sets our study apart is its integration of AI techniques not only for demand forecasting but also for generating high-level, decision-oriented insights. In particular, we develop a comprehensive framework that combines curve-fitting models with neural networks to predict demand type, determine the product’s life cycle stage, and generate stocking recommendations for new products. This integrated approach moves beyond traditional forecasting by supporting both strategic planning and operational decision-making, offering a practical and scalable tool for managing product portfolios more effectively.

Another key advantage of our study is the scale and diversity of our dataset, which includes 2,615 SKUs from a lighting products retailer. This is substantially larger than most prior studies (e.g., 30 SKUs in [22], 170 in [2], and just 6 in [32]). The size and richness of our data allow for the development of more robust, generalizable models, making our framework not only more accurate but also more reliable for real-world applications.

Table 1: Summary of Prior Research on PLC and Demand Forecasting

Study	Methodology	Application/Data	Key Limitations
[18]	Piecewise linear (triangle/trapezoid)	Ethical drug products (258 SKUs)	Limited generalizability; no AI or dynamic forecasting components
[12]	Diffusion model (Bass model)	Theoretical consumer durables model	Assumes homogeneous market; lacks adaptation to new categories or dynamics
[17]	Polynomial curve fitting (e.g., 2nd order)	Mississippi casino industry	Narrow domain; does not forecast for new products
[20]	Agent-based modeling	Different product categories (317 SKUs)	Focus on forecasting new product diffusion, lack of PLC modeling and demand forecasting
[21]	Data mining from reviews	E-commerce platforms	Investigate the diffusion pattern of a product based on review-signals; No PLC or demand forecasting for new product
[2]	Polynomial curve fitting + clustering	Dell computer products (170 SKUs)	Focus on PLC forecasting, Limited integration with AI for high-level operational insights
[32]	Fuzzy clustering+Deep learning	automobile products (6 SKUs)	Limited to demand forecasting of existing product; lacks PLC curve modeling
[22]	Clustering + Bass model	Consumer healthcare product from Philips (30 SKUs)	No integration with AI for high-level operational insights
[24]	ML + predictive modeling	Semiconductor components (425 SKUs)	Limited to demand forecasting; lacks PLC curve modeling
[33]	ANN, SVM, regression	Construction machinery spare parts (75 SKUs)	No PLC phase classification or lifecycle forecasting
[34]	ANN + domain knowledge	Small SUVs in Brazilian market (22 SKUs)	Limited to demand forecasting; lacks PLC curve modeling
[31]	Deep neural networks	Short life-cycle retail products (843 SKUs)	Black-box model; no interpretability or demand classification
[5]	Bayesian functional regression	Consumer products from JD.com (150 SKUs)	Requires extensive attribute data; complex implementation, No integration with AI for high-level operational insights
[23]	Curve fitting comparison (Bass, poly, linear)	Lighting retailer (2,618 SKUs)	Limited to PLC forecasting of existing product, No PLC or demand forecasting for new product, No integration with AI for high-level operational insights
[19]	Ensemble Bayesian functional regression	Intel Microprocessors (86 SKUs)	Requires extensive attribute data; complex implementation, No integration with AI for high-level operational insights, No benchmarking
[35]	Homogeneity-based clustering + ensemble ML	Smartphone sales data in South Korea (79 SKUs)	Limited to accuracy improvement for short life cycle products; Does not incorporate PLC forecasting; no demand class or stock decision prediction;
Our Study	Curve fitting (Bass, poly, linear) + clustering + neural networks	Lighting products retailer (2,615 SKUs)	Develop a framework to forecast PLC and demand of new products and integrate AI for high-level operational insights

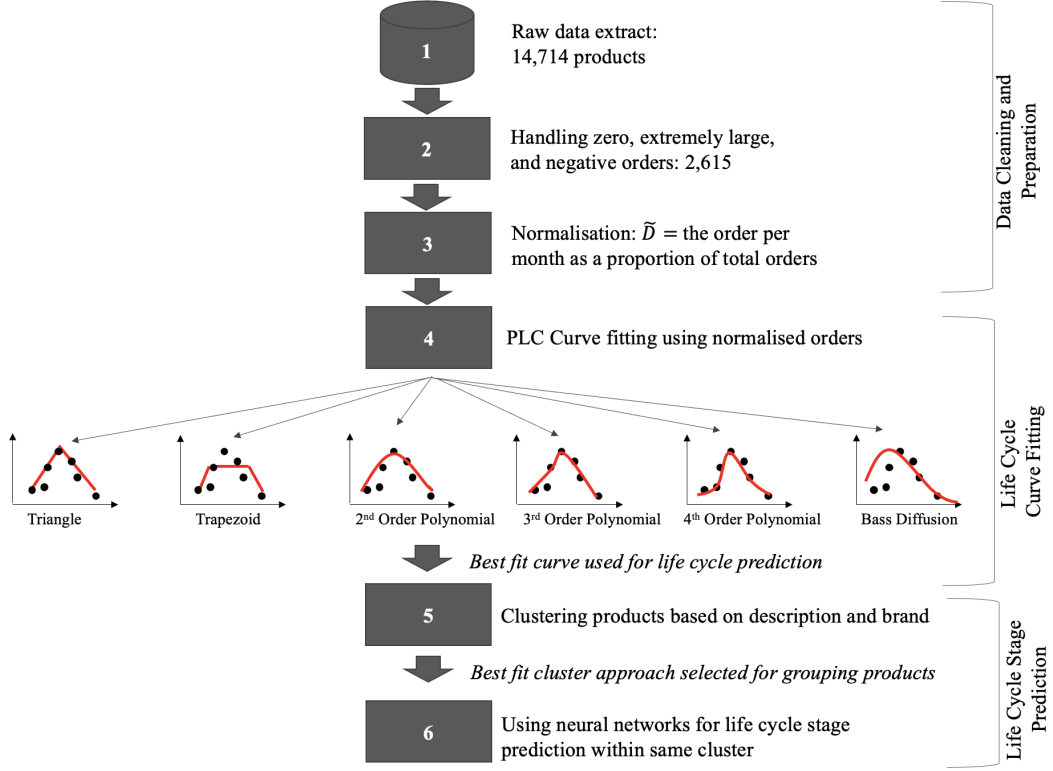


Figure 1: Methodology

3 Methodology

Our research methodology follows a systematic six-step approach. Figure 1 illustrates the forecasting framework, which consists of three key phases: data cleaning and preprocessing, PLC curve fitting, and PLC prediction.

Phase 1 focuses on integrating various methodologies to effectively prepare and refine raw data for analysis. Phase 2 applies different functions, including piecewise linear, polynomial, and Bass diffusion, to fit the PLC curve for each product. This curve-fitting process provides a detailed characterization of the dynamic evolution of each product's life cycle. Phase 3 leverages clustering techniques to predict the PLC curve of a new product and employs neural networks to determine its PLC stage, demand class, and stocking decisions.

3.1 Data cleaning and preparation

This section outlines the procedures to extract raw data and subsequently prepare and refine it for analysis. These sub-processes are shown in Figure 1, encompassing Steps 1 through 3.

In Step 1, we obtained the raw dataset from a retailer of lighting products using an SQL filter applied to its enterprise resource management system. For each Stock Keeping Unit (SKU), the dataset includes monthly cumulative customer orders, initial monthly forecasts, and categorical variables including demand class, life cycle

stage, and stocking status.

The demand class variable categorizes products into six levels: new, normal, lumpy, irregular, slow, and obsolete. Demand categories are retrieved from the system, and this is in line with [36] (a detailed explanation is presented in the appendix). The life cycle variable classifies items into three stages: growth, maturity, and decline. Additionally, a non-stocked variable indicates whether an item should be retained in inventory (i.e., during the growth and maturity phases) or phased out (i.e., at the end of its life cycle). This dataset, which the company had never cleaned, contains all SKUs recorded since the start of record-keeping, including many with zero demand during the selected analysis period.

In Step 2, we prepared the data to ensure accurate life cycle predictions by addressing inconsistencies such as negative orders, large bulk orders, and end-of-life processing. Following the approach in [37] and [2], we conducted the data preprocessing in three key stages.

First, we removed SKUs with no demand across the entire analysis period. Second, we excluded large bulk orders, which are likely associated with build-to-order processes, using outlier identification methods, since our focus is on customer orders that are made to stock. Third, we addressed negative orders, which often result from customer cancellations, using the algorithm in [37]. This algorithm mitigates the impact of negative orders while preserving the overall cumulative order quantity. The process involves iterating through time periods in both backward and forward passes. Initially, if we detect a negative order at time t , we replace the orders for that period and the previous period with the average of their original values. We repeat this process until we resolve all negative orders. Once no more negative orders remain, we set the cleaned orders as final.

In Step 3, after completing the data preparation process, we normalize the data using the max-min normalization method. This approach ensures that the cumulative sum of customer orders over a product’s lifetime is equal to 1. The resulting normalized customer order series, $\tilde{D}$, is obtained according to Eq. 1.

$$\tilde{D}_t^i = \frac{D_t^{p,i}}{\sum_{i=1}^{T_i} D_t^{p,i}} \quad (1)$$

where $D_t^{p,i}$ indicates the net customer order data for month t for SKU i after being prepared as previously mentioned, and T_i denotes the end-of-life cycle of SKU i . All subsequent analyses are carried out using the normalized data series, enabling us to compare the life cycles of products regardless of variation in their order volumes or lifetime duration.

3.2 PLC curve fitting

With cleaned and normalized customer order data, the next step involves fitting PLC curves to these datasets for each individual SKU (Step 4 in Figure 1). We use three main types of curves for this purpose: piecewise-linear curves

(including trapezoids and triangles as subsets), n-th order polynomial curves (poly-n), and Bass diffusion curves [5]. To ensure a comprehensive evaluation, we test and compare models from all three curve families, considering both fitting accuracy and model complexity. The parametric models are fitted to the 24-month demand data to enhance fitting performance.

3.2.1 Piecewise linear curves

Piecewise linear curves use connected straight-line segments to predict the life cycle. The triangle model consists of two connected line segments (Eq. 2) and requires four parameters (b_0, b_1, b_2, τ) , which are determined by Eq. 2.

$$\hat{D}_t = \begin{cases} b_1 t + b_0 & 0 < t < \tau \\ b_2(t - \tau) + (b_1 \tau + b_0) & \tau \leq t \leq T_i \end{cases} \quad (2)$$

where $\hat{D}_t$ represents the predicted customer order at period t , τ denotes the turning point, and (b_0, b_1, b_2) are the shape parameters optimized to minimize the difference between actual and predicted orders.

The trapezoid model consists of three connected line segments (Eq. 3), with the middle segment being flat, making it particularly suitable for products that have reached their maturity stage. The model requires five parameters $(b_0, b_1, b_2, \tau_1, \tau_2)$, which are determined by Eq. 3.

$$\hat{D}_t = \begin{cases} b_1 t + b_0 & 0 < t < \tau_1 \\ b_1 \tau_1 + b_0 & \tau_1 \leq t \leq \tau_2 \\ b_2(t - \tau_2) + (b_1 \tau_1 + b_0) & \tau_2 \leq t \leq T_i \end{cases} \quad (3)$$

Where $\hat{D}_t$ represents the predicted customer order at period t , τ_1 and τ_2 denote the start and end of the maturity stage, and (b_0, b_1, b_2) are the shape parameters.

3.2.2 Polynomial curves

Polynomial curves fit a smooth curve to the PLC. Polynomial functions up to the fourth order are considered for PLC prediction [2]. The n^{th} degree polynomial curve is given in Eq. 4.

$$\hat{D}_t^n = \sum_{i=0}^n a_i t^i \quad (4)$$

Where $\hat{D}_t^n$ is the predicted customer order at period t , and a_i for $i = 0, \dots, n$ are the shape parameters.

3.2.3 Bass diffusion function

The Bass diffusion function [12] models two effects that drive the adoption of a product in the population: Innovation (p), and Imitation (q). Innovators are early adopters of a product, drawn to technology regardless of who else is using it, and the demand generated from innovators peaks early in the life cycle. Imitators decide to adopt a product owing to the word-of-mouth effects; they are influenced by the behavior of others. The imitator demand peaks later in the life cycle. The market size, m , denotes the total demand for the product. The demand for the product at time t is denoted by $n(t)$. The cumulative demand up until time $t - 1$ is denoted by $N(t - 1)$. Then $n(t)$ can be calculated using Eq. 5, which is iterated into the future until there is no demand for the product. This period, where the demand is zero, indicates the end-of-life for the product.

$$n(t) = p[m - N(t - 1)] + q \left[\frac{N(t - 1)}{m} \right] [m - N(t - 1)] \quad (5)$$

Reorganizing Eq. 5, we have a regression equation with two independent variables, $N(t - 1)$ and $[N(t - 1)]^2$, in Eq. 6.

$$n(t) = pm + (q - p)N(t - 1) - \frac{q}{m}[N(t - 1)]^2 \quad (6)$$

The regression in Eq. 6 is used to estimate p , q , and m where the constant term, β_0 , is equal to pm . The coefficient of the first independent variable, β_1 , is equal to $q - p$, and the regression coefficient of the second independent variable, β_2 , is equal to $-q/m$. Then, rearranging terms, we find that the market size can be estimated using Eq. 7.

$$m = -\frac{\beta_1 \pm \sqrt{\beta_1^2 - 4\beta_2\beta_0}}{2\beta_2} \quad (7)$$

Once the parameters of the Bass function are fitted, we use them to estimate the life cycle of the product by running Eq. 5 iteratively until the demand at period t get sufficiently close to 0 (i.e., within 0.001 of 0); then we record the t as the end of life. We illustrate Bass diffusion function fits in Figure 2 for four products.

3.2.4 Assessing the PLC Curves

In Step 4, the parameters for each curve are determined by minimizing the root mean squared error (RMSE) between the given PLC curve and the customer order values over the weeks of the product's life cycle. RMSE is a widely used absolute error measure across various disciplines, including machine learning [38], PLC forecasting [2], data mining [39], and time series analysis [40]. This metric is mainly utilized for “model fitting (optimizing parameter selection for a specific model), model validation, model selection, model comparisons (among several competing models), and forecast evaluation” [41]. Moreover, the RMSE is more robust than the mean absolute error (MAE) because the

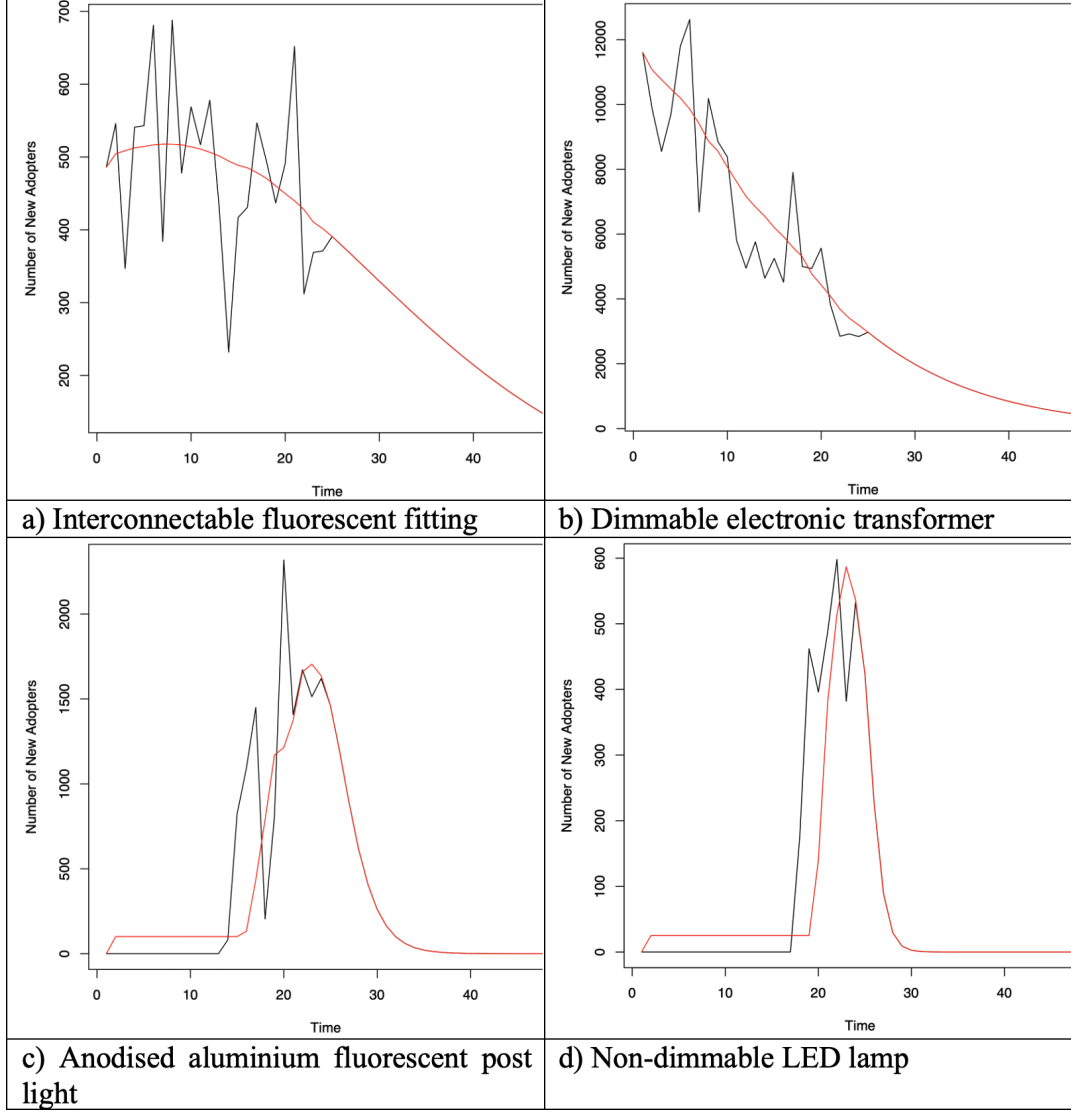


Figure 2: Illustration of Bass Diffusion Function on Sample Products

RMSE penalizes large errors while the MAE gives the same weight to all errors [2]. The RMSE serves a dual role: it is used not only for fitting the PLC curves but also for gauging the quality of the fit. Also, to evaluate and compare the relative quality of different curves, we use the Bayesian Information Criterion (BIC) [2, 5]. BIC is defined as $k \ln(n) - 2 \text{Loglikelihood}$, where Loglikelihood is the maximized log-likelihood of the model, k represents the total number of parameters to be estimated across all SKUs, and n denotes the total number of observations. BIC is a criterion for model selection among a set of candidate models, and it aims to strike a balance between a model's goodness of fit and the model's complexity [5]. The BIC penalizes complex models, which helps prevent overfitting by assigning a penalty for adding additional parameters [5]. A lower BIC value indicates a better trade-off between model fit and model simplicity, suggesting a simpler, more favorable model for the same accuracy [42]. According to the literature [43, 44, 45], the BIC is a widely used model selection metric that helps prevent overfitting by balancing

goodness of fit with model complexity. It is particularly well-suited for evaluating polynomial models.

3.3 PLC prediction of new products

In Steps 5 and 6, we apply various AI techniques to forecast the life cycle of new products. Step 5 utilizes clustering techniques to group PLCs of existing products and predict the monthly demand for each new product. This information is particularly valuable for operations managers in short-term planning, enabling more informed decisions on inventory levels, production schedules, and supply chain logistics.

Step 6 employs neural networks to predict demand class, PLC stage, and stocking status of new products. This high-level information is essential for operations managers in medium- to long-term decision-making. Accurate forecasting of these factors allows managers to better plan inventory needs, anticipate market trends, and make strategic decisions that improve operational efficiency and profitability.

By integrating these techniques, our approach provides a comprehensive demand forecasting framework that supports both immediate operational needs and long-term strategic planning. This dual focus helps businesses efficiently meet customer demands while optimizing resources and reducing costs.

3.3.1 Clustering

In Step 5, our forecasting process for new products consists of three key phases: clustering, forecasting, and accuracy evaluation. First, we use PLC curves derived from past products to predict the normalized demand for new products with similar characteristics. To identify relevant historical products, we apply a clustering technique, grouping products based on shared attributes. This clustering process helps determine which past products serve as suitable benchmarks for forecasting the demand for new products. Using the PLC curves of products within a cluster, we predict the PLC of a new product belonging to the same group.

To forecast monthly orders, we incorporate data from the fitted curves of similar products along with the company's knowledge of the new product's launch date and expected lifespan. The normalized PLC curve for a new product is determined using two approaches:

1. **Averaging Approach:** Computes the average of all PLC curves in a cluster on a step-by-step basis.
2. **Optimal Curve Approach:** Identifies the PLC curve within a cluster that minimizes RMSE and adopts it as the normalized forecast for new products in that cluster.

The normalized PLC curve is then converted into an actual forecast by scaling it based on time and volume for a 24-month period. Seasonality adjustments are not considered, as they are irrelevant to this product portfolio. For details on the methodology, we refer readers to [2].

To assess forecasting accuracy, we compare our demand estimates with the normalized demand of new SKUs that have sufficient predecessor information. As mentioned earlier, we exclude products from a cluster if their truncated end dates extend beyond the launch date of new SKU i . As a result, we adopt an out-of-sample methodology to evaluate the performance of our forecasting approach. Forecast accuracy is measured using two metrics: mean absolute scaled error (MASE) and sum of absolute errors (SAE). MASE is a scale-independent metric that allows for comparing forecast accuracy across different products. On the other hand, SAE offers a portfolio-wide accuracy measure but assigns greater weight to high-volume SKUs [2]. One significant advantage of the MASE metric over MAPE (Mean Absolute Percentage Error) is its ability to handle time series data with many zero values, as is the case in our study. Unlike MAPE, which produces infinite or undefined values when actual values are zero or near zero, MASE remains well-defined and reliable under these conditions, providing a more robust measure of forecast accuracy [46, 2, 47]. These characteristics make MASE and SAE well-suited for out-of-sample forecast evaluation, providing both a standardized comparison of accuracy and a practical focus on critical products within the portfolio.

The MASE and SAE for SKU i are obtained by Eq. 8 and Eq. 9, respectively.

$$MASE_i = \frac{\sum_{t=1}^{T_i} |\hat{D}_{it} - D_{it}|}{\left(\frac{T_i}{T_i-1}\right) \sum_{t=2}^{T_i} |\hat{D}_{it} - D_{it-1}|} \quad (8)$$

$$SAE_i = \sum_{t=1}^{T_i} |\hat{D}_{it} - D_{it}| \quad (9)$$

Where $\hat{D}_{it}$ represents the normalized demand estimation by our prediction method for SKU i at month t , and D_{it} denotes the normalized net customer demand for SKU i during month t . Additionally, T_i refers to the estimated end of the life cycle for SKU i . While curve fitting provides accurate demand volume forecasts for new products, high-level operational decisions, such as how to classify demand types, identify PLC stages, or decide whether to stock a product, require a more flexible classification approach. To address this, we incorporate artificial neural networks (ANNs) as the final step in our framework. These models use the normalized PLC forecasts as inputs and generate actionable classifications for demand, inventory, and lifecycle decisions.

3.3.2 Neural network

Typically, it is difficult to obtain precise numerical predictions of the demand for new products. Instead, decisions need to be made based on an operational approximation [48, 34]. This approach allows managers to quickly gauge the potential success of a new product, identify any risks or opportunities associated with its introduction, and adjust their strategies accordingly. Therefore, in Step 6, we use the normalized demand forecast for new products obtained in Step 5 to make predictions about three critical aspects: demand classification, specific PLC stage, and the decision

to stock or not stock the product. This process helps categorize products based on their expected demand levels, identify their position within the PLC, and determine the most appropriate inventory strategy.

We use neural network modeling to predict these three critical aspects because it aligns with the level of approximation that high-level managers need. Neural networks can capture complex patterns in the data. ANNs have garnered significant attention from both practitioners and researchers in recent years, primarily due to their ability to learn complex non-linear relationships from data without relying on distributional assumptions [49]. An ANN is composed of a set of interconnected neurons (input and output units) organized into layers that map inputs to outputs by learning the underlying relationships between them [50]. The hidden layer, through activation functions, performs nonlinear transformations of linear combinations of the inputs, which are then used to model the output [51]. To illustrate how a neural network model produces a predicted output from given inputs, we present the mathematical formulation of a three-layer feedforward neural network:

$$h_j = f\left(\sum_{i=1}^n w_{ij}x_i + b_j\right) \quad (10)$$

$$\hat{y} = g\left(\sum_{j=1}^m \nu_j h_j + b\right) \quad (11)$$

Equation 10 represents the transformation from the input layer to the hidden layer. Here, x_i denotes the input features, where $i = 1, 2, \dots, n$, and h_j is the output of the hidden node j , where $j = 1, 2, \dots, m$. The total number of input features is n , and the hidden layer consists of m nodes. The weights connecting input i to hidden node j are represented by w_{ij} , and each hidden node has an associated bias term b_j . The hidden layer applies a nonlinear activation function $f(\cdot)$ to the weighted sum of its inputs. Common activation functions include the sigmoid, rectified linear unit (ReLU), and softmax functions [51].

Equation 11 describes the transformation from the hidden layer to the output layer. The weights connecting hidden node j to the output node are denoted by ν_j , and the output layer includes a bias term b . The function $g(\cdot)$ is the activation function applied at the output layer (e.g., identity, sigmoid, or softmax). The final predicted output of the network, $\hat{y}$, is computed using Equation 11.

The exponential increase of data available to companies, coupled with significant decreases in the cost of computing power, has made artificial intelligence approaches more relevant and applicable in business. Neural network modeling is a powerful approach in the field of artificial intelligence and machine learning. This technique has gained prominence due to its ability to automatically learn patterns and representations from data, making it highly effective for tasks such as predictive modeling [52]. Unlike traditional statistical techniques, which often rely on predefined assumptions and linear relationships, neural networks can capture complex nonlinear dependencies within data [49]. The capacity of neural networks to learn from data, identify complex patterns, and process unstructured information provides them

with a significant advantage over conventional statistical methods [49, 53]. This enables more accurate and flexible solutions compared to traditional models, such as Auto Regressive Integrated Moving Average (ARIMA), across a wide range of applications. The superiority of neural networks in these contexts has been consistently demonstrated and validated in prior research [54, 55, 49].

There is a misconception that neural networks are solely applicable to large datasets. Numerous significant factors related to neural network modeling need to be considered. The size of the data set stands as one of these factors, while the count of variables represents another pivotal aspect. In a broader context, the accuracy of modeling outcomes can be best assessed by examining the errors for both the training data and the test data. Hence, even with a limited dataset, neural network modeling has the potential to yield favorable results, contingent on the characteristics of the dataset. A notable example is the use of neural network modeling for small datasets; for example, pharmaceutical companies such as Biogen use it for handling small batch sizes of materials [52]. The body of literature concerning neural network modeling is vast. A comprehensive exploration of this approach can be found in [56]. Together with the curve-fitting and clustering steps, the neural network models complete an integrated framework that supports both quantitative forecasting and qualitative decision-making for new product management.

4 Findings

4.1 Descriptive Statistics

The raw dataset contained 14,714 SKUs spanning a 24-month period from June 2012 to May 2014. After completing the data preparation process, which involved handling SKUs with zero demand, removing large bulk orders, and addressing negative orders, we obtained a final dataset of 2,615 SKUs with no negative orders, enhancing the reliability and quality of our subsequent analysis. The products were broadly categorized into four groups: LEDs, lights, lamps, and complementary products. Complementary products comprise parts such as bezels, switches, and cables. We estimate the launch time of each SKU by considering the first month with positive demand. The PLC length of each SKU is determined using the Bass diffusion function.

Table 2 presents summary statistics of the data after preparation. The demand distribution is skewed toward higher values, and PLC durations vary across products. The data indicate that 75% of the products fall within an “intermediate” life cycle (more than two years), meaning their lifespan is longer than short-term or fast-moving items but not as extensive as long-life-cycle products. While our methodology is broadly applicable across industries, our findings are specific to the industrial setting of this study. In the cleaned dataset, 30% of SKUs are in the growth stage, 65% in the maturity stage, and 5% in the decline stage of their life cycle.

Table 2: Summary of statistics of the data after preparation

	Mean	Standard Deviation	25 th	50 th	Percentile 75 th	99 th
Monthly customer orders	236	1132	0	7	73	380
Predicted life (months)	32	20	16	25	44	71

Table 3: Summary of statistics of the data after preparation

Fitted Curve	Average RMSE	Average BIC	# SKUs for Best RMSE	# SKUs for Best BIC
Triangle	0.050	-137.768	28	680
Trapezoid	0.051	-130.718	0	13
2nd Order Polynomial	0.029	-83.767	2	0
3rd Order Polynomial	0.037	-82.700	59	0
4th Order Polynomial	0.036	-81.780	1840	0
Bass Diffusion	0.038	-149.437	686	1922

4.2 Quality of PLC Curve Fitting

The quality of fit for each curve in Step 4 is presented in Table 3. The Trapezoid piecewise linear function was never the best fit. The Triangle function yielded the lowest error for 28 products (1.1%). The 2nd-order polynomial was the best fit for only two SKUs, while the 3rd-order polynomial was optimal for 59 SKUs (2% of the portfolio). The majority of SKUs (1,840, or 70% of the portfolio) were best represented by the 4th-order polynomial. The Bass function provided the best fit for the remaining 686 SKUs (26%).

Both the Trapezoid and Triangle curves have similar average RMSE values, with the Triangle curve performing slightly better (0.050 vs. 0.051). These results indicate that while both curves offer comparable prediction accuracy, the Triangle curve is preferred based on the trade-off between fit accuracy and model simplicity, as reflected in the Average BIC value.

In comparison, the polynomial curves outperform piecewise linear curves and the Bass diffusion curve in RMSE, indicating better predictive accuracy. However, their higher BIC values suggest potential issues with overfitting. This outcome suggests that polynomial curves might be overly complex in some cases. The Bass diffusion curve, despite having slightly higher RMSE values, achieves a better balance between prediction accuracy and model simplicity, as reflected by its lower BIC. Thus, the Bass diffusion curve seems to be the best fit for predicting the life cycle of products in this context, given its ability to provide reasonably accurate predictions while maintaining a simpler model structure.

Consistent with the findings of [2] and [5], the 4th-order polynomial yields the lowest RMSE among existing parametric curves and remains consistent across SKUs. However, the performance gap between the 4th-order polynomial and piecewise linear models tends to be larger. It is important to note that the Bass diffusion function does not

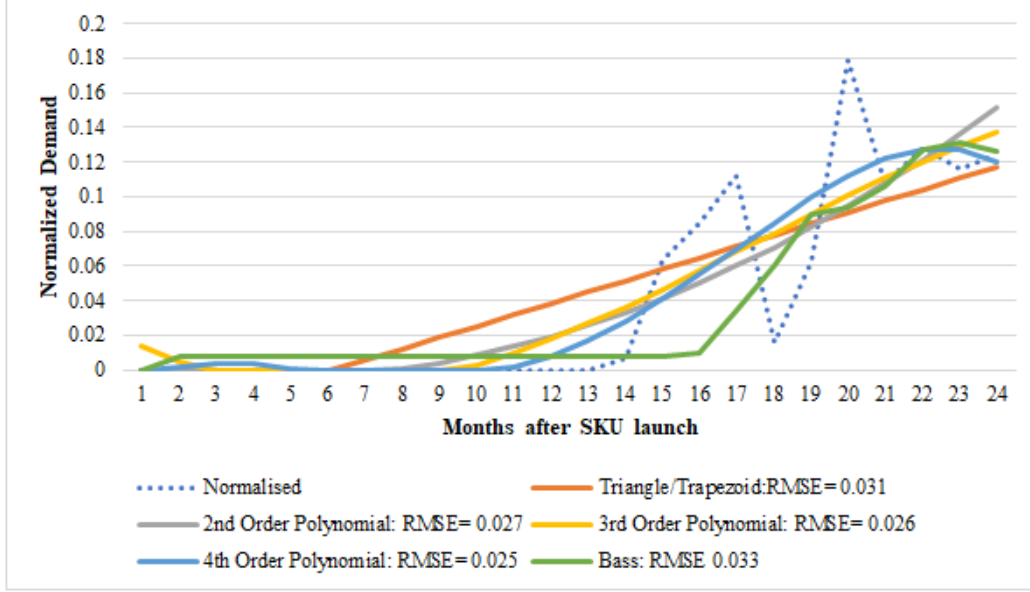


Figure 3: Comparison of fit curves for a specific product: anodized aluminum fluorescent post light

Table 4: Distribution of products into clusters

	# of SKUs	% of SKUs	Min Life	Average Life	Std. Dev. Life
Lights	1010	39%	11	43.2	24.4
LEDs	648	25%	11	40.9	24.7
Lamps	483	18%	9	40.5	23.3
Complementary Products	474	18%	14	47.7	24.0
Total	2615	100%	9	42.9	24.3

always produce a valid fit; we successfully applied it to 2,213 SKUs (85% of SKUs in the portfolio).

Figure 3 presents a fit comparison for a specific product (anodized aluminum fluorescent post light). In this figure, the Triangle and Trapezoid piecewise linear curves produced identical estimations, while the 4th-order polynomial provided the best fit. Once the best-fit curve for an SKU is identified, it is used to predict orders beyond the analysis period (from the 25th month onward).

4.3 Clustering of Existing Products and PLC Forecasting of New Products

Based on product definitions, we cluster 2,615 products into four clusters: 1) lights, 2) LEDs, 3) lamps, and 4) complementary products that are needed to install lights, LEDs, or lamps. The distribution of products into these clusters is given in Table 4, where the product-life duration is given in months.

Based on product definitions, we categorize 2,615 products into four clusters: (1) lights, (2) LEDs, (3) lamps, and (4) complementary products required for the installation of lights, LEDs, or lamps. The distribution of products

Table 5: Distribution of the best PLC fitted in each cluster

	Triangle	Trapezoid	Percentage of SKUs			
			2 nd Order Poly.	3 rd Order Poly.	4 th Order Poly.	Bass
Lights	0	17.0	0.1	1.0	59.3	22.6
LEDs	0	16.8	0.2	1.7	65.6	15.7
Lamps	0	15.9	0.0	1.9	65.0	17.2
Complementary Products	0	13.5	0	2.1	66.7	17.7

Table 6: Distribution of new SKUs into clusters

	# of SKUs	% of SKUs	Min Life	Average Life	Std. Dev. Life
Lights	72	26%	12	32.6	13
LEDs	91	33%	14	31.4	13.1
Lamps	70	25%	12	33	12.9
Complementary Products	45	16%	12	32.8	12.9

across these clusters is shown in Table 4, where product life duration is measured in months. The “Complementary Products” category has the highest average end-of-life value, suggesting that these items are likely to have a longer life cycle than others.

We also attempted clustering based on brand names, but this approach did not yield meaningful results. The clustering produced 14 small groups with fewer than 10 products each, while a single cluster contained 2,352 products (90% of SKUs), limiting its usefulness. Table 5 presents the percentage of SKUs in each cluster for which the fitted curve is identified as the optimal choice based on RMSE. Notably, the high prevalence of 4th-order polynomial and Bass curves across all clusters underscores their effectiveness in capturing the demand dynamics of these products.

The distribution of new SKUs across categories is presented in Table 6. To predict the normalized PLC for a new SKU i , we refine the forecast by excluding all products within its cluster that have a truncated end date extending beyond its launch date. This prevents the forecast from being influenced by future information that could bias the results.

As a result of this out-of-sample filtering, the number of predecessor SKUs varies across clusters. SKUs with no predecessors or only one predecessor are excluded from the analysis, yielding a final dataset of 278 SKUs for PLC forecasting and accuracy evaluation. Figure 4 illustrates the forecasted PLC curve for two distinct forecasting methods applied to a new SKU, alongside a comparison with the normalized demand.

To evaluate the accuracy of our forecasting, we compare our estimation of the demand with normalized demand for 278 SKUs for which we have adequate predecessor information. We use an out-of-sample methodology to evaluate the accuracy of our forecasting: we assess the accuracy using MASE and SAE. Table 7 presents the out-of-sample

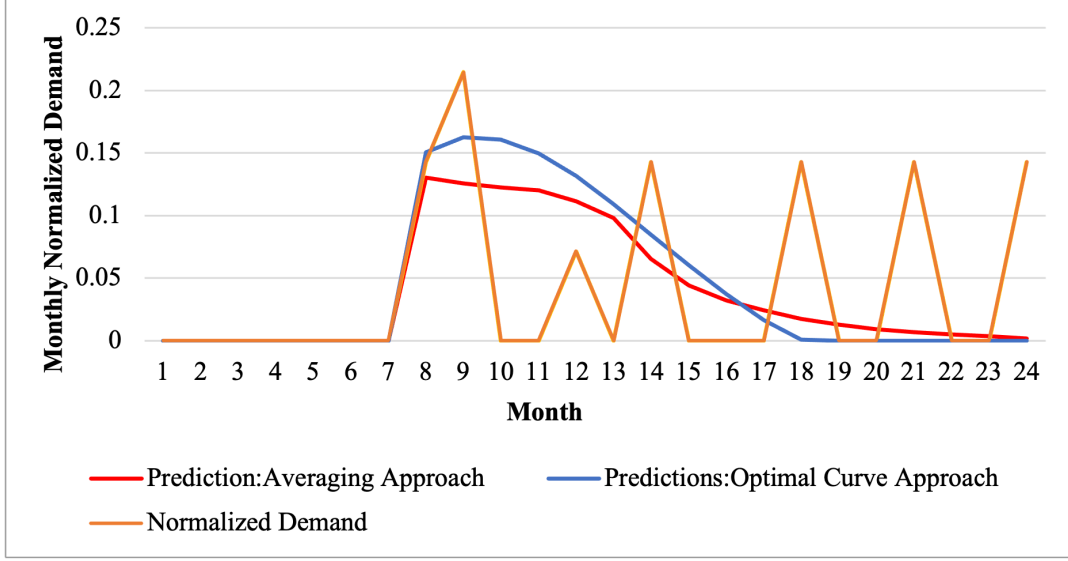


Figure 4: Forecasted PLC curves using averaging (red) and optimal curve (blue) approaches for a new SKU

Table 7: Out-of-sample accuracy for different forecasting approaches

	Averaging Approach		Optimal Curve Approach	
	MASE	SAE	MASE	SAE
Lights	1.55	1.73	1.67	1.89
LEDs	1.66	1.7	1.81	1.89
Lamps	1.77	1.7	1.89	1.90
Complementary Products	1.98	1.73	2.12	1.89

average RMSE and SAE to evaluate the accuracy of our forecasting approaches across all SKUs in each cluster. The consistency of MASE and SAE values across both approaches demonstrates that our forecasting methodology is robust in the face of diverse clustering patterns.

4.4 Artificial Neural Network Models

The ANN model was configured to predict three key output variables. First, it performs demand classification, categorizing the product’s demand level. Second, it identifies the product’s life cycle stage, classifying which phase of the life cycle the product is currently in. Third, it predicts the stocked vs. non-stocked decision, determining whether replenishment is required.

The normalized demand forecasts serve as input variables, enabling the neural network to generate precise and actionable predictions, which support managerial decision-making in inventory management and sales planning. We utilized 24 months of normalized projected demand data derived in Step 3 of the methodology. This duration was selected based on our analysis of product life cycle data (see Table 2 or Table 6), which indicated that a significant

proportion of products exhibit life cycles exceeding two years. Incorporating this time frame ensures that the model captures critical demand trends over the typical life span of the products.

The ANN models were developed using SPSS software (version 28), which facilitated the optimization of key parameters, such as the number of hidden layers, transfer functions, and hidden nodes. Three distinct neural network models were constructed, each tailored to predict one of the output variables. The dataset was divided into a training set (70%) and a test set (30%). The training process was governed by a stopping rule, defined as one consecutive step with no decrease in error. This approach ensured efficient training without overfitting [57, 58] and reduced the computation time [49]. The number of nodes in each hidden layer was determined according to the model's requirements [59].

Since all three output variables involve multiclass classification, Cross-Entropy Error was used as the loss function for model evaluation [60, 2], as shown in Eq. 12. In this formula, K is the number of classes, y_i is the true label, and $\hat{y}_i$ is the predicted probability for class i . This metric, widely applied in classification tasks, quantifies the divergence between predicted probabilities and actual labels [61, 60]. Compared to Mean Squared Error (MSE), cross-entropy provides advantages in learning rate and convergence, as its steeper gradient enhances optimization when predicted outputs deviate significantly from actual values. Given its demonstrated effectiveness in classification, cross-entropy was selected for this study.

$$L(y, \hat{y}) = - \sum_{i=1}^K y_i \log(\hat{y}_i) \quad (12)$$

We encountered an issue with imbalanced data for the demand-class variable, which we addressed through over-sampling. Specifically, the original dataset for new products contained 173 records for demand Class 1 (Normal), 38 records for Class 2 (Lumpy), and 58 records for Class 4 (Irregular). Imbalanced datasets pose challenges when examining complex relationships among diverse variables [62], as machine learning algorithms tend to favor the majority class, leading to biased results and poor classification of minority classes [63]. To mitigate this, we employed resampling, a common technique for handling imbalanced data, which involves either oversampling minority classes or under-sampling the majority class to achieve a balanced distribution [2].

In our approach, we oversampled the minority classes (Classes 2 and 4). For each demand class, we calculated the average, maximum, and minimum values for the 24 input variables representing predicted demand over 24 periods. To generate additional samples, we determined the difference in record counts between Classes 1 and 2 (i.e., 173 - 38) and created new samples by interpolating uniformly between the average-to-maximum and average-to-minimum values. This process increased the number of records for Class 2 from 38 to 165. A similar methodology was applied to Class 4, increasing its sample size to address the imbalance in the dataset. The performance and accuracy results for neural network modeling indicated that this oversampling approach effectively addressed the imbalance.

4.4.1 Demand Class Prediction

The model summary is presented in Table 8, column titled ‘Demand Class’. The best results were achieved when there was one hidden layer, seventeen hidden units in the hidden layer, and the activation function was hyperbolic tangent for the hidden layer and softmax for the output layer. The validation phase of the model on the test dataset demonstrates a prediction accuracy of 87.5%.

The results from Table 8, column ‘Demand Class’ indicate the successful recognition of patterns between inputs and outputs (demand class) during the training phase. The percentage of error during the testing phase is lower compared to the error observed during the training phase. In cases where the model is not effectively trained, a significant percentage of error is typically observed in the test dataset. The stopping rule was based on observing a sequence of one consecutive step(s) with no reduction in error.

Table 8: Neural network model summaries for ‘Demand class’, ‘Stocking decision’, and ‘PLC stage’

Prediction	Training		Testing		ANN Architecture
	Cross-Entropy Error	% Incorrect	Cross-Entropy Error	% Incorrect	
Demand Class	113.2	16.4%	40.0	12.5%	1 hidden layer, 17 nodes, Softmax activation
Stocking Decision	103.3	30.6%	49.9	32.6%	1 hidden layer, 17 nodes, Softmax activation
PLC Stage	81.9	18.3%	36.5	18.1%	1 hidden layer, 17 nodes, Softmax activation

4.4.2 Predicting whether a product should be stocked or not

The model summary is in Table 8, Column titled ‘Stocking Decision’. The validation phase of the model on the test dataset shows a prediction accuracy of 67.4%. The best results were achieved when there was one hidden layer, and seventeen hidden units in the hidden layer, the activation function was hyperbolic tangent for the hidden layer and Softmax for the output layer. The similarity between test and training performance suggests that the model achieved relatively good pattern recognition. Otherwise, the test dataset could exhibit a significant level of error when compared to the training set.

4.4.3 PLC Stage Prediction

The model summary results are in Table 8, column titled ‘Life Cycle Stage’. The best results were achieved when there was one hidden layer, and seventeen hidden units in the hidden layer, the hyperbolic tangent was the activation function in the hidden layer, and Softmax was the activation function in the output layer. The validation phase of the model on the test data set shows a prediction accuracy of 82%. It is crucial for management to determine the PLC stage of a product, which impacts all inventory management, warehousing, and budget management.

As demonstrated in predicting demand class, stocking decisions, and PLC stages, the single-hidden-layer neural network consistently outperformed other architectures. This observation aligns with prior research showing that single-hidden-layer neural networks perform well in demand forecasting tasks [64, 49]. These models offer a promising approach, with their primary strength being the ability to generalize complex non-linear functions without relying on distributional assumptions [64, 49].

5 Conclusion and Managerial Implications

In this research, we develop a PLC-curve forecasting framework for new products, harnessing the power of AI. Predicting demand for products with a short life cycle becomes more accurate when early market feedback is incorporated into the forecast models. This invaluable information allows for more precise projections, enhancing decision-making and resource allocation. However, when dealing with products in the intermediate PLC category, the forecasting landscape is nuanced. While initial market signals still hold importance, the longer duration of the product’s life cycle introduces additional variables that can impact demand trends. Therefore, using AI allows us to not only capture initial market feedback but also continuously gather and interpret data throughout a product’s life cycle. By doing so, we can identify changing trends, external influences, and customer preferences that might affect demand over time. This comprehensive approach ensures that our forecasting adapts to the evolving situation, helping us manage inventory smartly and maintain customer satisfaction as the product remains relevant.

5.1 Managerial Implications

This work presents an accurate, scalable, and interpretable framework for forecasting the PLC of new products, especially those with limited or no historical sales data. Calibrated with real-world data from a large UK-based lighting retailer, the model builds upon, but significantly advances, existing industry practices. Traditionally, firms rely on heuristic methods to estimate demand for new products by identifying “comparable” items and applying simple averaging techniques [5]. While intuitive, such approaches lack precision and adaptability.

Our framework formalizes this logic into a data-driven, AI-enhanced decision support system. It begins by clustering existing products based on their market function and sales dynamics. Then, it fits PLC curves, such as polynomial or Bass diffusion functions, to each cluster and applies either a cluster-average or best-fit approach to forecasting the life cycle of a new product within that cluster. Importantly, this method improves forecast accuracy without requiring external data inputs, making it highly practical and scalable. A key innovation is the use of artificial neural networks to translate the normalized forecast into actionable classifications, including demand class, life cycle stage, and stocking decisions. This allows managers not only to anticipate overall product performance but also to make timely operational decisions across inventory planning, marketing, and product portfolio strategy.

Although our empirical study focuses on the lighting industry in the UK, the framework is easily transferable to other industries or geographical contexts. The only requirement is access to basic internal product data (e.g., SKU-level sales volume, product category, or function). It is also particularly suitable for firms operating in environments where external market benchmarks are unavailable or unreliable. Furthermore, because the model is designed to function effectively with limited sales data, it is well-suited for use with short-life cycle or newly launched products, including those that have not yet accumulated a sales history. This cold-start capability enhances its usefulness in fast-paced or innovation-driven industries. For geographical adaptation, localized variables (e.g., seasonality, regional consumer preferences, or product categories) can be incorporated into the clustering process or used as input features in the neural network model. To implement this framework effectively, operations managers should follow several practical steps:

- Establish robust data infrastructure: Firms must ensure that detailed sales and inventory data are recorded systematically for each SKU across its life cycle. This historical data is essential for both clustering and curve-fitting processes that underlie the PLC forecast.
- Use similarity-based clustering for new product forecasting: Managers should forecast the PLC of a new product by identifying historical clusters of products with similar functional attributes or sales patterns. This is especially valuable for intermediate life cycle products that exhibit demand behavior shared across many SKUs. Because the model leverages internal data, it avoids dependence on external macroeconomic or consumer behavior inputs.
- Balance complexity and interpretability in model selection: While more complex models (e.g., 4th-order polynomial curves) may offer high accuracy, simpler models (e.g., Bass diffusion) often provide better interpretability and reduce the risk of overfitting. Especially in contexts with limited data or short product life cycles, managers should prioritize models that balance goodness of fit with parsimony. Tools like BIC are useful for this purpose.

This study offers several managerial implications grounded in empirical results and designed to improve product lifecycle forecasting, demand classification, and inventory decisions in retail operations.

1. Managers can use internal product data to forecast the PLC of new products, even before launch. Unlike traditional forecasting models that rely on post-launch sales data, our results (Table 7) show that curve-fitting models trained on clusters of similar historical products can effectively predict sales volumes for new SKUs. This enables retailers to make data-informed stocking and marketing decisions early in the product lifecycle, even in cold-start conditions.
2. Different products require different PLC models for accurate forecasting. Our findings show that no single PLC curve fits all products well: fourth-order polynomial models worked best for 63% of the products, while

Bass and piecewise linear models were optimal for others. Managers should therefore avoid relying on a single model across the board and instead adopt a hybrid or data-driven selection process based on product category and historical patterns.

3. Neural networks provide actionable insights by classifying products, not just predicting sales. In addition to forecasting sales volumes, our neural network model accurately classifies each product by demand type (normal, lumpy, or irregular), PLC stage (introduction, growth, maturity, decline), and stocking recommendation (stock or do not stock), as shown in Table 8. These classifications help managers make more targeted decisions, such as adjusting inventory levels for lumpy demand items, planning end-of-life strategies for declining products, or avoiding overstocking products with low forecast performance.
4. Our integrated forecasting framework reduces reliance on external market data. The combination of curve fitting, product clustering, and neural network classification in our framework enables accurate forecasting and decision-making using only internal product and sales data. As demonstrated in our analysis, all inputs in our framework are derived from internal product and sales data. For managers in fast-moving retail environments where external benchmarks are scarce or delayed, this offers a robust and scalable alternative for forecasting and planning.

Beyond these implementations, the framework yields several strategic and operational insights:

Accurate PLC prediction is crucial for both manufacturers and retailers to make informed inventory decisions and develop effective sales strategies throughout a product’s existence. Manufacturers must align production schedules and shipments with sales forecasts prior to new product launches. Similarly, retailers are tasked with determining order quantities and optimal inventory allocation to meet customer demand efficiently [5]. One of the reasons that AI can boost the performance of operations in companies is the complexity of intertwined activities, whether among different units and entities of a company (e.g., production line, warehousing department, planning department, sales, and marketing) or other entities outside of the companies such as supply chain networks.

Managers can plan production, inventory, staffing, and marketing based on projected demand at different stages of the PLC. This prevents over- or under- investment in resources, optimizing operational efficiency [6]. Similarly, understanding the PLC helps managers determine when to invest in research and development for new features, improvements, or entirely new products. Early-stage investment might be necessary to sustain the growth phase, while late-stage investment could focus on extending the product’s decline phase. In addition, the PLC plays a pivotal role in strategic warranty management by integrating technical and commercial considerations from product conception to obsolescence [65]. Manufacturers and retailers can share the necessary information to predict PLCs and plan accordingly for new products [8].

Accurate PLC prediction helps managers avoid excessive inventory build-up, especially as the product moves

from growth to maturity. This prevents excess stock from becoming obsolete during the decline phase. Inventory decisions are closely related to marketing decisions, which should be aligned with the PLC. The early stages might require awareness-building campaigns, while the later stages may need repositioning, rebranding, or highlighting the unique features of the product to maintain customer interest [66]. In a similar way, accurate PLC prediction helps in developing exit strategies for products in their declining phase [7]. Managers can plan for discontinuation or phase-out, ensuring a smooth transition for customers, employees, and stakeholders [67].

Moreover, our research suggests that incorporating demand classification into forecasting processes, particularly using neural network models to categorize demand as normal, lumpy, or irregular, can offer substantial operational benefits. Traditional inventory systems often assume continuous or uniform demand across all products, leading to inefficiencies in stock control. Demand classification schemes help match demand patterns with the most suitable forecasting techniques. Our analysis highlights that accurately forecasting demand type can support more effective stocking decisions and, as supported by the literature, may lead to significant reductions in inventory costs [53].

PLC prediction relies on data analysis and modeling. This data-driven approach can guide operations managers in making informed decisions about asset management, maintenance schedules, and upgrades. Such decisions are more likely to lead to resilient outcomes than relying solely on intuition or outdated practices [5]. Incorporating these perspectives into strategic decision-making enables companies to navigate the challenges and opportunities presented by each stage of a PLC, leading to improved competitiveness, sustainable growth, and enhanced overall performance.

5.2 Limitations

One of the potential directions for future research involves addressing the limitation of using data exclusively from a single retailer. Expanding the data set to include various industry sectors could improve the robustness and applicability of PLC prediction models. This extension would offer a more comprehensive understanding of the dynamics at play, contributing to the generalizability and accuracy of the predictions. Another research avenue can be to incorporate promotion or seasonal impact on PLC forecasting. There is potential in exploring the use of diverse non-parametric models for predicting PLC curves. This exploration would involve assessing the accuracy of these models in comparison to existing parametric models. In our PLC predictions, we solely relied on sales records to classify products into growth, maturity, and decline stages. Where available, using customer reviews could provide valuable external data. Deep learning-based time-series analysis techniques have been found to provide early closure warnings for businesses, and how customer reviews can be incorporated into predicting the PLC stage is an open research question. Additionally, other classification and AI tools could be utilized for comparison with the performance of neural network modeling, further enhancing the robustness and applicability of the proposed approach. Future research could also explore the integration of PLC forecasting with the life cycle costing and environmental

life cycle assessment. Aligning PLC-based demand and inventory predictions with sustainability metrics and cost considerations would provide a more holistic decision-support framework.

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6 Appendix

Demand categories are retrieved from the system. They are calculated in line with [36], where each category is assigned based on the squared coefficient of variation (CV^2) and average inter-demand interval (p), except for new and obsolete SKUs, categories of which are decided by the system user. The squared coefficient of variation is calculated only for positive demand; in other words, periods with zero demand are ignored in its calculation. The cut-off values for CV^2 and p are 0.49 and 1.32, as in [36]. If a product has $CV^2 \leq 0.49$ and $p \leq 1.32$, then it is categorised as normal. If it has $CV^2 > 0.49$ and $p \leq 1.32$, then it is irregular. If it has $CV^2 \leq 0.49$ and $p > 1.32$, then it is slow. Finally, if it has $CV^2 > 0.49$ and $p > 1.32$, then it is lumpy.



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Life cycle prediction: a comparison of methods for a lighting products retailer

Aktas, Emel; Chomachaei, Fahimeh; Golmohammadi, Davood

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