

# A Decision-Support System for New Product Sales Forecasting

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## ABSTRACT

This study proposes the New Product Sales Forecasting Procedure (NPSFP) and the New Product Forecasting System (NPFPS) for solving the new product sales forecasting problem. The NPSFP standardizes the steps involved in sales forecasting, guiding data acquisition and analysis, choice of the forecasting model, calculation of the actual forecasts, and subjective manual adjustment of the forecasting results. The NPFPS decision-support system includes four modules: one that guides data acquisition and analysis, one that contains forecasting model templates, one that helps the users choose the best model for the available data, and one that calculates and adjusts the actual forecasts.

**Keywords:** Demand Management, Demand Forecasting, New Product Sales Forecasts, New Product Forecast Procedure, New Product Forecast System, Heuristic Algorithm

## INTRODUCTION

Introducing new products can provide a competitive advantage as well as a long-term financial return on investment [9]. New product development is thus vitally linked to a company's competitive strategy and consequently to the new product sales forecasting that provides quantitative information on the expected return from development efforts. Sales forecasting attempts to decrease uncertainty, providing input for the decisions made about introducing of new products and offering feedback for the new product development process [9]. The significant correlation between new product development and new product sales forecasts makes new product forecasting extremely important.

Many companies cite new product forecasting as one of the most difficult forecasting problems they encounter. Such forecasting involves taking a blind leap into the future because there is little or no historical data to provide guidance [6]. The high degree of uncertainty involved when introducing new products just adds to the difficulty of new product forecasting. Inaccurate forecasts could lead to erroneous business decisions, which could in turn result in excess inventory or significant inventory shortages. More importantly, new products have a longer lead time than existing products because, given no knowledge of the future, most supply chain partners maintain low inventory levels, or even no inventory, despite the fact that a rapid reaction to the market is essential for the successful introduction of new products. In light of the above discussion, a complete system for new product forecasting is urgently needed.

Numerous forecasting techniques are available to sales forecasting managers [1, 4, 6, 8]. Based on these characteristics, there are three broad categories of sales forecasting methods: Qualitative, Time Series, and Correlation [4, 6]. Qualitative forecasting methods are primarily subjective and rely on forecaster experience [1, 4, 6, 8]. Time Series forecasting methods—Moving Average and Exponential Smoothing are the most popular—use historical demand information to make forecasts, assuming that past demand patterns will be a good indicator of future sales [1, 4, 6, 8]. Correlation forecasting methods—Regression analysis is the most commonly used—find the correlation between demands and environmental factors, for example, the correlation between economic conditions and demands [4, 8].

Several studies have focused on the data shortage issue for a completely new-to-the-market product by

incorporating market information, market research data, and subjective assessments into their forecasting models. Morrison [7] studied the implementation of diffusion models to forecast sales of a completely new-to-the-market product. He projected future sales with a non-linear symmetric logistic curve, using three parameters: the long-run saturation level, the inflection point of the diffusion curve, and the delay factor. He produced good results with his model; nevertheless, the assumption of continuous growth before inflection and the symmetric shape of the logistic curve should be examined further because not all new-to-the-market products have these characteristics.

Goldfisher *et al.* [2] proposed a method for determining the success or failure of a new product, which allowed weekly forecasts to be performed using only three weeks of data. They defined a Sales Index (SI) as a percentage of the difference in sales between two consecutive periods. Their study used Sales Forecast Ratios to predict future sales using SI. However, their approach relied heavily on sales data for only a few time periods, which may not be appropriate for new product sales forecasts, which involve a high degree of uncertainty.

McLean *et al.* [5] also presented a method for dealing with limited data using truncated Taylor Series. The authors assumed that the forecasting function could be represented by a Taylor Series and that the most important components of the expansion were the first few derivatives. Hence, the prediction for the future sales was formulated as a weighted sum of historical sales. More weight was assigned to more recent data, while less weight was assigned to older data.

There are several ways to measure forecast performance, including evaluating the forecast results in terms of accuracy, error, cost, efficiency, profit, and/or customer satisfaction. Common measurements (e.g., Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Error (MSE)) have all been used by companies to assess the forecasting function [3, 4].

Kahn [3] reported that, according to an industry survey, 48% of the respondents used MAPE to measure forecast accuracy, while 13% used MAD and 2% used MSE. Based on his survey, Kahn concluded that the average acceptable forecast accuracy for necessary SKU (stock keeping unit) levels was 77% (MAPE) across all industries and 76% (MAPE) for the consumer product industry specifically. This study will also apply the modified MAPE to the Evaluation module for evaluating the performance of this system.

The rest of the paper is organized as follows. Section 2 describes the procedure for the new product forecast and proposes a decision support system, called New Product Forecast System (NPFS), to help this task. Section 3 shows the results of NPFS on a real-world case. Finally, Section 4 offers our conclusions and our suggestions for future research.

## NEW PRODUCT FORECASTING SYSTEM (NPFS)

This study aims to solve the new product sales forecasting problem. However, no standard procedure for new product sales forecasting currently exists. Therefore, we propose a procedure that standardizes the steps from data collection to the final subjective adjustments of the forecast results.

### Step 1: Collect and Analyze Data

Different types of data related to new product forecasts are required and must be collected in step 1. Forecasts are usually based on past product sales patterns; however, with new products, it is difficult to observe any pattern since very little historical sales data is available. In this first step, forecasters should focus on increasing the quantity of the input data so that at least three sales data periods are available. In addition to increasing the data quantity, in this step, the data quality should also be improved by attempting to reduce the variation and identifying the leading indicators.

## **Step 2: Determine Parameters for Forecasting Methods and Select the Best Forecasting Method**

In step 2, the parameters for each forecast method must be determined. Different forecasting methods require different parameters, which have a direct impact on the forecast results. In the procedure proposed in this study, we use the Mean Absolute Percentage Error (MAPE) as the evaluation standard for selecting a method. Experienced forecasters who know the market well can later help to decide whether or not to adjust the results subjectively. Companies can also define rules or indices for altering the results. The evaluation rules for forecast accuracy are based not only on the historic sales data, but also on the weighted average heuristic.

## **Step 3: Calculate Sales Forecast**

Once the parameters and the forecasting method have been determined, the forecast is calculated according to the desired planning horizon—short-term, mid-term, and/or long-term. For instance, when managers make long-term strategic decisions, such as picking the location for a new factory site, they need a rough idea of the future sales trends and thus sales forecasts for the next year could be appreciated. On the other hand, short-term decisions are facilitated by daily and weekly sales forecasts.

## **Step 4: Adjust Results Subjectively**

Experienced managers or forecasters often adjust the forecast results manually. The survey results of Sanders *et al.* [8] showed that more than 80% of the respondents adjust quantitative forecast results based on their subjective judgment. Professional managers often have their own perceptions of future trends based on the events occurring on the market and their industry experience. Consequently, step 4 allows managers to make adjustments, with the final results being used for future planning for a variety of purposes at the end of forecast procedure.

The tasks in steps 1, 2 and 3 of the above procedure are facilitated by a decision-support system called New Product Forecast System (NPFS). This decision-support system comprises four modules that provide functions for the forecasting tasks so that users don't have to be experts in business forecasting techniques. There are three major difficulties inherent to new product sales forecasts: dealing with limited data, using the forecasting methods, and selecting the best method to use. The four modules of decision-support system shown in Figure 1—Data Handling, Forecasting Model, Learning Platform and Forecasting—can tackle these three problems.

### **■ Data Handling Module**

The *data handling* module is responsible for dealing with the limited data problem. Because new products have been recently introduced on the market, little or no sales data are available for analysis. It is thus necessary to find substitute data in order to calculate the sales forecast. There are many external factors that can affect sales, including special events and promotional events. For this reason, in addition to finding substitute data, this module focuses on improving the quality of input data by identifying these external factors and prepares the input data for processing by the *forecasting model* module. The *data handling* module produces at least three periods of sales data, either from its own historic data or from the historic data of items in the same class. This data, together with all the parameters needed for each forecast method, are send on to the *forecasting model* module.

### **■ Forecasting Model Module**

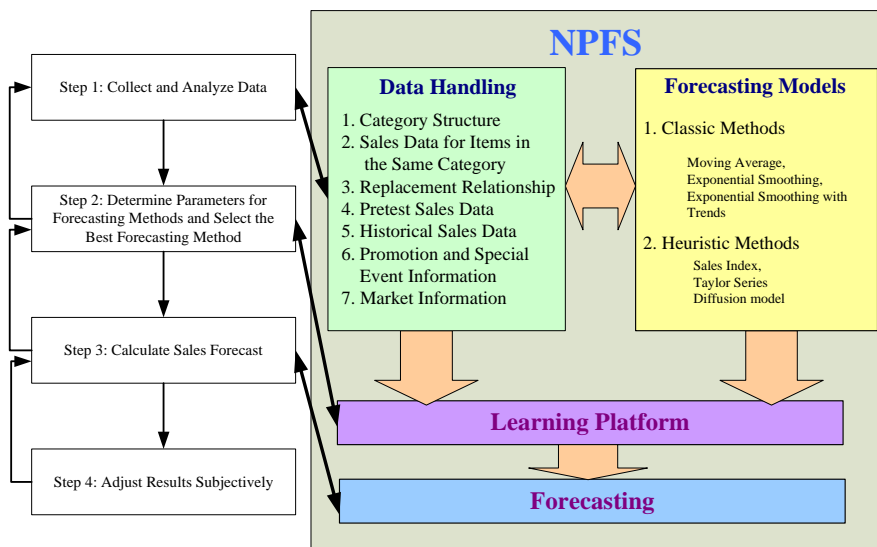
Unlike sales forecasts for mature products with a stable demand, the most difficult problem with new product sales forecasting is the lack of historical data. Because newly introduced products have no historic behavior to be traced, Regression is not appropriate for new product forecasting [11] and thus was not included in the NPFS decision-support system. N-period Moving Average, Exponential Smoothing, and Exponential Smoothing With Trends (an extension of Exponential Smoothing), though

predicting the future sales based on a product’s historic patterns, require only a few data points and thus were included in our system [11]. In addition, the NPFS decision-support system includes all three of the new product forecasting methods presented in our literature review: Sales Index, Diffusion Model, and truncated Taylor Series. Each of these methods have their own limitations, and thus we have modified them for use in our NPFS system. By the end of processing in the *forecasting module*, for each new product, there is a choice of at least six methods, each with multiple parameter selections.

■ **Learning Platform**

The *learning platform* module provides an automatic learning platform that uses input from *data handling* module and *forecasting model* module. It determines the best parameters for each method and then chooses the most appropriate method for future sales forecasting according to most current available data. When sales occur and new historical data are input into NPFS, the *learning platform* module is activated again and selects the most appropriate method for the current situation. The final method selected, together with its best parameters, is used for future forecasts

Figure 1: The Architecture of New Product Forecast System (NPFS)



■ **Forecasting**

Once the *learning platform* module has selected the best forecasting method and the best parameters for each new product, the *forecasting* module then computes the future sales forecast. The resulting forecast will become the basis for future planning [9], which can be long-term, mid-term and short-term. Future sales forecasts may focus on different geographical levels (e.g., country, region, city, and store) or different time dimensions (e.g., yearly, quarterly, monthly, weekly, and daily). In order to meet different planning objectives, the *forecasting* module predicts future sales for different combinations of these two dimensions.

**TESTING NPFS ON REAL-WORLD CASES**

This section demonstrates the applicability of NPFS using two real-world problems, involving two retail company selling different kinds of products: tea and cosmetics. The first case deals with new tea products. The data used was provided by a leading tea company in Taiwan, whose business encompasses the planting, producing, and retailing of tea. In addition, this leading tea company has started serving “tea meals” in their shops in recent years. As of April of 2007, the company had 133 chain stores all over Taiwan. The date for introducing new tea products depends on the tea leaf picking

season—winter or spring. A successful tea product can be sold for years. Three successful new tea products that had good initial sales periods in 2006 were used to compare the NPFS forecast results with the results of the commonly-used Moving Average method. The information about these three new products from different classes is given in Table 1. Two of the new products have an appropriate number of actual data points, while one has data points for only 2 periods.

Table 1 shows the NPFS result and Moving Average (MA) result. Judging by the future MAPE, the NPFS forecast is better than the MA forecast. NPFS chose the ES method for two of the new products and the SI method for the last new product because the sales of the item 450XX followed a pattern similar to other products in the same class. The result for the new tea products also agrees with the scenario analysis conclusion that the number of actual data points affects the forecast accuracy.

Table 1: Forecast Results using NPFS and MA for the New Tea Products

Item No	Classification	Number of Actual Data Points	Method*	Parameter	Future MAPE	Difference
336XX	Oolong Tea (Intense Scent)	5	ES	0.1	4.173%	-15.102%
			MA	3	19.275%	
448XX	Special Tea	4	ES	0.1	16.508%	-14.423%
			MA	3	30.931%	
450XX	Oolong Tea (Light Scent)	2	SI	1	21.39%	-24.198%
			MA	1	45.588%	

\*The forecasting method is represented by the following abbreviations: DF = Diffusion Model; ES = Exponential Smoothing; EST = Exponential Smoothing with Trend; MA = Moving Average; SI = Sales Index; TY = Taylor Series.

The second case deals with new cosmetic products. The data used was provided by a leading chain drugstore with more than 100 stores across Taiwan. Five successful new cosmetic products from different classes were selected to test the applicability of NPFS (Table 2). These products had been sold in the leading chain drugstore in 2006.

Table 2: NPFS and MA Forecasts for the New Cosmetic Products

Item No	Classification	Number of Actual Data Points	Method*	Parameter	Future MAPE	Difference
6262XX	Special Skin Care	2	SI	1	10.371%	-64.366%
			MA	1	74.737%	
9935XX	Lipstick	7	MA	2	11.388%	-1.539%
			MA	3	12.927%	
6372XX	Basic Skin Care	2	ES	0.1	16.076%	-23.676%
			MA	3	39.752%	
6356XX	Basic Skin Care	2	ES	0.1	17.983%	-6.32%
			MA	1	24.303%	
6314XX	Facial Foundation	2	SI	1	26.948%	-3.207%
			MA	1	30.155%	

\*The forecasting method is represented by the following abbreviations: DF = Diffusion Model; ES = Exponential Smoothing; EST = Exponential Smoothing with Trend; MA = Moving Average; SI = Sales Index; TY = Taylor Series.

Cosmetics are such a competitive business that hundreds of new products are launched every year to satisfy customer needs. The lifecycle of a cosmetic product is short, and the demand is usually unstable. As shown in Table 2, most of the new products used in this test had only a few actual data points. Table 2 reports the NPFS results and the MA results. Because the demand was unstable, ES was selected for three of the products and SI for the other two. The forecast produced by NPFS is obviously better than

the one produced by the MA method based on the future MAPE.

The results for these two real-world cases show that NPFS forecasts are better than those of the commonly used MA method.

## CONCLUSION

New product sales forecast usually depends on the decisions of experienced managers, such as decisions about the selection of the forecasting model when only limited data is available. Instead of relying on human judgments, this study introduces a standard forecast procedure offering a general work flow to perform forecast. In addition, New Product Forecast System (NPFS) is proposed to help executing the standard forecast procedure for new product sales forecast. A prototype of NPFS is constructed to evaluate the performance. NPFS is applied to a real-world case of cosmetics. In this case, several successful products in different classes were tested and the forecast result showed that NPFS had better performance than the commonly used methods. It can be concluded that the commonly used methods that widely adopted in practice is not suitable one to be used in new product forecast.

More real-world cases—such as consumer electronics and fashion products—should be tried because they introduce different types of new products every seasons. Furthermore, this study only include quantitative models in NPFS. The qualitative model which considers consumer behavior should also be included in NPFS in the future to boost the forecast accuracy. Some product characteristics—color, style, or special design—affect the sales of products significantly and thus should be identified and quantified in NPFS in the future to help product classification or future sales forecast.

## Acknowledgements

This research was sponsored by the National Science Committee of Taiwan, under the project number NSC 96-2416-H-002-015.

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