# Change&Chance Embraced

# ACHIEVING AGILITY WITH SMARTER FORECASTING IN THE SUPPLY CHAIN

HANS LEVENBACH, PhD

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#### Preface

For some time now, the use of computerized and improved statistical forecasting methodologies has greatly enhanced the productivity and effectiveness of forecasting in business, government and private sectors around the world. This development is in part driven by the changing and uncertain nature in competitive markets, global economic disruptions, financial objectives, shifting demographics, and operational environments facing a business enterprise.

The clear need for improved business planning to reduce costs, increase profitability and enhance customer satisfaction, for instance, has increased the desire to apply better forecast modeling approaches to the planning and management of **change and uncertainty** in the supply chain.

Fortunately for supply chain practitioners, data-driven predictive analytics have greatly simplified and speeded up the way they can make their planning forecasts. Ready access to large data sources, automated statistical modeling, cheap computing and increasingly sophisticated quantitative techniques have given rise to a wide variety of modern data-intensive techniques that are applicable in a relatively short time at a reasonable cost. Still, a practitioner can easily be overwhelmed by a plethora of forecasting techniques that are not readily understood or well implemented. Moreover, the manager and end-user of the forecasting process have been offered little training in how to make more effective and appropriate use of these powerful (often inadequately documented) techniques in real-world situations.

#### Demand Forecasting: A Data-Driven Process

Up to recent times, **business forecasting** has been closely linked to economic and financial analysis. During the 1980's, however, economic forecasting suffered from a lack of credibility, media ridicule and shortcomings in accuracy goals. Nowadays, the meaning of business forecasting has broadened considerably to include forecasting a *consumer data-driven* demand for products and services throughout a supply chain from supplier of raw material to consumer of finished goods. Called **demand forecasting**, it generally attempts to predict future consumer/customer demand for a company's goods and services.

This modern focus is nowadays directed more to forecasting the disaggregated elements of product demand for supplying warehouses, distributors, channels, customer accounts, and consumers than to economic- and financial-driven aggregates. Demand forecasting, within the context of this book, means that the firm attempts to predict the *right* amount of the *right* product to be in the *right* place at the *right* time for the *right* price, which is one of the underpinnings of what is now known as **demand forecasting and replenishment planning** for the supply chain.

By presenting a unified and practical orientation to demand forecasting, this book aims to prepare a practicing forecaster or student learning about demand forecasting to become a productive professional. To this end, I present the most widely accepted, currently practiced quantitative and qualitative techniques in business forecasting. The principal unifying theme of this book is the presentation of forecasting as a process, rather than a series of disconnected techniques. A further unifying theme is a constant emphasis on the role and importance of looking at data, or **exploratory data analysis**, as practiced by statisticians and scientists.

The industrial examples and computer spreadsheet exercises included herein are also consistent with the goal of preparing the reader for the immediate practice of demand forecasting as a data-driven process.

### What Is New?

This book is a complete revision of the 2005 book **Forecasting – Practice and Process for Demand Management** and its 1984 predecessor **The Modern Forecaster**, coauthored with James P. Cleary. Although basic principles underlying the demand forecasting process have not changed, a sea change has occurred to forecasting in the business environment from top-down macroeconomic forecasting to bottom-up operational forecasting. This has meant a realignment of major topics as well as the introduction of new material based on bottom-up data structures for large database applications.

### Scope

In this book, I have introduced the following:

- Establishment of a *structured data framework* for an agile demand forecasting process. Specific methodologies and practical techniques are presented within the context of the overall process.
- Selection of the forecasting and analytical techniques *most appropriate* for any given problem, based on *forecast profiles*, rather than model fitting. The techniques discussed, many representing current state-of-the-art, are the ones that have proved to be most useful and reliable to practicing forecasters.
- *Exploratory analysis of historical data* before attempting to create models and forecasts. Computer-generated graphical displays enable you to see in a picture what you might otherwise have to glean from a spreadsheet.
- Performance of *diagnostic analyses on both fit and forecast errors*. To determine what the unexplained variation might tell us about the adequacy of the model and the uncertainty in the forecast, I stress the importance and usefulness of displaying residual diagnostics and forecast error distributions. Residuals and forecast errors from hold-out samples are emphasized throughout as essential in all phases of an effective model-building effort.
- Using robust/resistant methods to complement traditional methods. Experience with a wide variety of realistic applications has convinced me that data are rarely well behaved enough for the direct application of standard statistical assumptions. The robust/resistant methods produce results that are less subject to departures from conventional normality assumptions and to the distortions caused by a few outlying or unusual data values. By creating both traditional and robust/resistant results, the practitioner is in a better position to decide which are the most appropriate for the problem at hand.
- Refocusing the attention of practitioners away from the *mechanistic execution of computer software* and *the manipulation of model fit parameters* toward a greater understanding of data, data quality, forecast profiles, and business context.
- Embracing forecast numbers with measured uncertainty in forecasting as a key ingredient to achieving agility and credibility with demand forecasting among planning organizations and with trading partners. The field sales input, collaboration with partners and customers, and the Sales and Operations process helps assure that the forecaster's role as *advisor* achieves forecast accuracy, credibility, and acceptance with management and forecast-users.

This book describes a number of basic, well-established and proven forecasting methodologies that are applicable to a wide variety of real-world business applications. The practicing demand forecaster will find that the techniques explained in this book provide preliminary models necessary for achieving improvements before building increasingly complex models. Likewise, managers and end users of forecasts will find in this book a comprehensive treatment of how to evaluate basic forecasting approaches. In addition, the material offers a guide (including checklists) to using, interpreting, and communicating practical forecasting results.

For the practicing demand forecaster and planner, student, and researcher, the book will be of interest because it extends the basic principles to meet the need of the experienced forecaster. The development of the book progresses in a natural fashion from the basic, most-widely used techniques to the more sophisticated, less familiar techniques. In this progression, the book includes up-to-date statistical forecasting tools in exploratory data analysis, structured data management, elements of robust/resistant estimation, exception handling and root-cause diagnostics, and state-space forecasting models.

This book shows how to analyze and forecast variables by emphasizing basic forecasting techniques. It begins the analysis with traditional approaches and follows them with resistant (those that safeguard against outliers and unusual values) and robust (those that safeguard against departures from classical statistical assumptions) alternatives to the same problems. More advanced techniques, including the ARIMA (Autoregressive-Integrated-Moving Average) models based on the Box-Jenkins methodology, and some dynamic regression and econometric modeling with multiple variables, are considered as well. However, some more esoteric techniques, such as neural networks, vector autoregression, and GARCH, are not included because they appear to be more relevant in applications to financial business and macroeconomic forecasting.

Many examples are drawn from the experience of practicing forecasters, teachers and consultants in industry. My personal experience suggests that modern demand forecasting applications contain a common thread independent of the particular supply chain or industry. That is, the characteristics of the data and the structured modeling steps required are vital to the understanding of any forecasting technique. However, as I stress throughout the book, the context of the business problem must not be forgotten; it plays a vital role throughout the forecasting endeavor. Data sets from a variety of real company sources have also been used throughout to make certain points or illustrate a particular technique.

#### Coverage

My experience suggests that, in practice, the failure of many forecasting efforts begins with flaws in the quality and handling of data rather than in the lack of modeling sophistication. Thus, my objective has been to place greater emphasis on data-analytic methodology (much of it intuitive and graphical) as a key to improved demand forecasting.

A number of forecasting techniques useful to students and researchers of forecasting are not covered in great detail in this book. The omitted techniques are typically used when quantitative data are scarce or nonexistent. As an example, the whole field of technological forecasting, which requires grounding in probabilistic (in contrast to data-analytic) statistical concepts, is not treated. Because this book deals with exploratory data analysis along with confirmatory modeling, I have emphasized techniques for which a reasonable amount of data is available or can be collected.

The focus and emphasis on formal statistical approaches for empirical work in most forecasting books are rooted in the days of limited computing power and data storage capability. Much of the subject matter in those texts are mathematically elegant; others are designed to make it easy for the instructor to provide packaged lectures, problem exercises and test questions. My experience in the corporate world suggests that statistical theory tends to be over-emphasized at the expense of data analysis with real data. Although not grounded as firmly in theory, simpler approaches can frequently do as well as, and at times surprisingly better than, their complex cousins.

The computer has made it feasible to warehouse lots of relevant data in 'big data' repositories and process complex predictive analytic algorithms in a flash, or in the cloud, as the case may be. We are now able to effectively analyze ever-larger amounts of data, much of this through graphical means and data mining techniques from data warehouses/cloud-based data repositories, in shorter timeframes than ever before. We are entering the petabyte (PB =  $10^{15}$  bytes) era on the way to the yottabyte (YB =  $10^{24}$  bytes) of data storage capability. The availability of relevant data, simple paradigms, and the experience of individual demand forecasters needs to be more balanced than ever before.

Economics, mathematics and mathematical statistics have provided much of the formal underpinnings and rationale in the demand forecasting practice before the widespread availability of desktop computing power. As a result, certain statistical tools omitted in this book, such as hypothesis testing, in fact, are not really required for demand forecasting because confidence measures and prediction intervals give, for all practical purposes, identical results and are closer to the business realities. I understand this goes along with some recent trends occurring in statistics curricula for business students.

#### Courseware

The material in this book can be used for turnkey courses and workshops for enhancing the professional skills of forecasters performing the demand forecasting function in supply chain environments. I can suggest three courses here:

- A. Introduction to Demand Forecasting (IDF)
  - **Target population**: This course is intended for entry-level forecasters and forecast users requiring a working knowledge and understanding of market and demand forecasting in the modern supply chain. This course is also recommended for managers in sales, marketing, budgeting, human resources and operational organizations, who require an appreciation in the use of quantitative and qualitative forecasting techniques.
  - **Description:** IDF is designed to provide the hands-on skills for dealing effectively with the principles and techniques of data analysis, graphical presentation and interpretation of forecasting models and results. The course focuses on those forecasting techniques for products and services that have become the most widely accepted and prominently used by forecasters in industry. Topics are drawn from chapters 1 - 8, 12, 14.
- B. Data Analysis and Forecast Modeling (DAFM)
  - **Target Population**: This course is intended for intermediate forecasters and analysts with some background and experience in quantitative analyses. This course is also recommended for managers in sales, marketing, budgeting, human resources and operational organizations, who require a sound foundation in the use of statistical modeling tools for macro-level forecasting applications.
  - **Description:** DAFM is designed to provide the enhanced statistical skills for understanding the theoretical and empirical foundations upon which data analysis and statistical forecasting models are based. This course focuses on skill-based techniques for exploratory data analysis, data quality, data visualization, trend/seasonal time series models, regression/econometric applications, residuals and forecast error analysis, and presentation of results occurring in a

broad range of industrial forecasting applications. Topics are drawn from the following chapters: 1-11.

- C. Agile Demand Forecasting (ADF)
  - **Target Population**: This course is intended for the experienced forecasters and analysts with at least two years of active involvement in demand forecasting at the corporate level. Some background and experience in quantitative modeling and analysis is highly desirable.
  - **Description**: ADF is designed to provide automated, databased forecasting simulations of realworld demand forecasting applications in the cloud. The material covers techniques for exploratory data analysis, data quality, database management, predictive visualization, chance distributions, automated forecast modeling, regression/econometric modeling, residual analysis, and presentation of results occurring in a broad range of demand forecasting applications in industry. Topics are drawn from the following chapters: 1-14.

Other options for using this material include:

- **Train-the-Trainer Services**. Enable organizations to achieve a quick, effective start-up of training to provide timely services for new hires, organizational changes or redeployment of resources.
- Customized Training. Courses can be adapted to provide specific modules addressing the needs
  of distinct audiences involved in forecasting: power users, casual users of forecasts, managerial
  users, and new hires.
- **On-site Training**. Same courses held at a corporate training facility.
- Training an Installed Base on software upgrades. Provide continuity of usage of forecasting software systems adopted by forecasting organizations.

#### Organization

This book is divided into five parts. The first part **Framing the Demand Forecasting Process** is comprised of four chapters on how to start making a forecast, introducing the demand forecasting process along with preliminary data analysis, a classification of forecasting techniques, and forecast accuracy measurement. The three chapters of Part II cover **Exploring Historical Data** with chapters on characterizing demand variability in terms of: seasonality, trend, and the uncertainty factor; dealing with seasonal fluctuations, and forecasting trend-cycles with turning points. The next two chapters in Part III concern **Automated Forecasting Techniques: The State-Space Approach** with chapters on baseline forecasting with exponential smoothing models and the comprehensive Box-Jenkins methodology for the ARIMA family of univariate linear models. In Part IV on **Creating Causal Forecasting Models**, two chapters cover demand forecasting with regression models and gaining credibility through root cause analysis and exception handling. These techniques are used primarily for short-term, operational forecasting applications with causal factors. Part V (**Improving Forecasting Agility: The PEER Process**) treats the examination and management needs in acquiring agility in demand forecasting performance. These three chapters deal with delivering the final forecast numbers; creating a data framework for Agile Forecasting<sup>®</sup> and decision support, and blending Agile Forecasting<sup>®</sup> with an integrated business planning process.

#### DEDICATION

I would very much like to thank my wonderful wife Suzanne and my family, for their patience and understanding of yet another distraction into writing a book.

#### ACKNOWLEDGMENTS

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One contributor from my 38-year association with the *International Institute of Forecasters (IIF)* has enabled me to include a variety of Excel-based tools that form the basis for the hands-on portions of the CPDF<sup>®</sup> professional development workshops for supply chain practitioners that I have been conducting over the last decade around the world: Everette S. Gardner, Jr. (University of Houston) was instrumental in introducing spreadsheet forecasting tools for students and practitioners. Ev also pioneered and implemented the first automated statistical forecasting algorithms that illustrate many of the practical forecasting and data analytic tools used throughout this book. Also, Len Tashman, (University of Vermont) generously provided examples from his work on forecast accuracy measurement and forecast simulation methods.

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Forgive me for an unintended senior moment if I left someone out.

Hans Levenbach, PhD

Morristown, NJ USA

November, 2017

# WHY DEMAND FORECASTING IS SO IMPORTANT TO SUPPLY CHAIN PROFESSIONALS

The Supply Chain

#### 1. Analyzing Customer Demand: What should we make and when?

Based on customer demand, product design, cost, and pricing considerations, the ice cream manufacturer (as in Cases 1A, 3A–8A, 10A, 13A–15A) sets the supply chain in motion. For instance, cocoa beans for making chocolate will be sourced from Africa or South America.



agreements. This results in lead-time variation in demand patterns.

# AND MANAGERS IN THE GLOBAL SUPPLY CHAIN OF AN ICE CREAM MANUFACTURER



Accurate forecasts assure that the right amount of the right product is available to consumers when they need it. Poor forecasts can lead to overstocks, out-of-stocks and loss of profit.

# Why Demand Forecasting is So Important to Supply Chain Professionals and Managers

The earth is degenerating these days. Bribery and corruption abound. Children no longer mind parents. Every man wants to write a book, and it is evident that the end of the world is approaching fast.

#### ATTRIBUTED TO AN ANCIENT TEXT

This introductory chapter describes

- what a demand forecasting process is
- why it is a necessary discipline for demand planners and managers to become familiar with
- a new role for demand managers in a modern, consumer data-driven supply chain
- how, when, where, and by whom the demand forecasting job is done
- the systematic steps for an agile execution of the demand forecasting process in the supply chain

As you begin to read this book, you may find it helpful to keep the following in mind:

- A grasp of economics, demographics, computer science and statistics, although necessary for a demand forecaster, will not in itself ensure successful demand forecasting practices.
- For the best results, apply such knowledge within a sound framework—a demand-forecasting process.
- Following a sound process, which describes the sequence of activities to be followed, can reduce chances of inadvertently overlooking a key step.
- The omission of a key step, whether deliberate or inadvertent, can jeopardize a forecaster's credibility, and credibility is a forecaster's livelihood.

After reading this chapter, you should be able to

- create a visual representation of your business in relation to sources of demand for products and services in the industry and how it links to the consumer (end user) or customer (organization/account)
- understand the motivation behind exploring and quantifying sources of variation in demand
- create graphical representations of the variation in demand in terms (economic consumer habit), trend (demographic consumer growth), and other quantifiable factors, including uncertainty.

#### Inside the Crystal Ball



A wise person once said that he/she who lives by the crystal ball soon learns to eat ground glass. The same sage left this advice for all managers pressed to provide their corporate bosses with projections: Give them a number or give them a date, but never give them both. Unfortunately, those in the business of forecasting the **demand** for products and services must provide both numbers and a timeline.

# Determinants of Demand

Economists have long attempted to determine what causes people to behave as they do in the marketplace. Over the years, one aspect of this research has evolved into a theory of demand. In theory, demand expresses the inverse relationship between price and quantity; it shows the maximum amount of money consumers are willing and able to pay for each additional unit of some commodity, or the maximum amount of the commodity they are willing and able to purchase at a given price. There may not be enough of the commodity available to satisfy the demand. Economists concern themselves not with a single item purchased by members of a group (a market) but rather with a continuous flow of purchases by that group. Therefore, demand is expressed in terms of the amount desired per hour, per day, per month, or per year.

There are a number of **determinants of demand**. The demand for international holiday tourism, for instance, is known to depend on a number of factors including (a) the origin population (the higher the number of people resident in a country, the greater the number of trips taken abroad), (b) origin country real income and personal disposable income, (c) cost of travel to the destination and the cost of living for the tourist in the destination, and (d) a relative price index relating substitution between tourist visits to a foreign destination and domestic tourism.

Demand varies with tastes, total market size, average income, distribution of income, the price of the good or service, and the prices of competing and complementary goods.

#### **Demand Forecasting Defined**

The simplest definition of forecasting is that it is a process that has as its objective the prediction of future events or conditions. More precisely, forecasting attempts to predict change in the presence of uncertainty. Demand Forecasting is all about change and chance. If future events represented only a quantifiable change from historical events, future events or chance conditions could be readily predicted through quantitative projections of historical patterns into the future. Methodologies that are used to describe historical events with mathematical equations (or models) for the purpose of predicting future events are classified as quantitative modeling techniques. However, there is much more to forecasting than projecting past trends.

Forecasting is a process that has as its objective the prediction of future events or conditions in the presence of uncertainty.

Experience and intuitive reasoning quickly reveal that future events or chance conditions are not solely a function of historical patterns. Even familiar abstractions such as trend, cycle, and seasonality, although extremely useful to business planners, cannot be completely relied upon when it comes to predicting future events. In addition, in the commercial world, goods and services are bought by individuals for innumerable reasons. Therefore, demand forecasting must include other ingredients to complement quantitative modeling techniques.

A demand forecast is not an end product but rather an input to an integrated business planning process. A demand forecast provides advice to planners and decision-makers as to what is likely to happen under an assumed set of circumstances. Often, a forecast is a prediction of future values of one or more variables under "business as usual" conditions. In planning activities, this is often referred to as the status quo or the baseline. Forecasts are also required for a variety of "what if" situations and for the formulation of business plans to alter base case projections that have proved unsatisfactory.

# Demand forecasting is the process of predicting future consumer and customer demand for a firm's goods and services with quantified uncertainty.

#### Why Demand Forecasting?

Forecasting for demand planning and management in the supply chain generally attempts to predict future consumer/customer demand for a firm's goods and services. Customers tend to be loosely defined as either consumers (individuals at checkout counters) or accounts through which goods or services are ordered. For some time, this process had been closely linked to sales and marketing. Within the corporation, sales forecasting has suffered from a lack of credibility, corporate ridicule, and shortcomings in accuracy. Within the marketplace, business media have commented on the inability of economic forecasters to predict recessions, as per the 1996 Fortune writer who said, "The biggest problem with macro-economic forecasters is that they generally can't tell us what we most want to know."

So, why bother with forecasting? It is generally recognized that accurate, credible forecasts are necessary to provide significant improvements in manufacturing, distribution, and the operations of retail firms. Over time, demand forecasting has become much more focused on the disaggregate elements of product demand for supplying warehouses, distributors, channels, and consumers than on economic and financially driven aggregates. In recent times, the scope of demand forecasting has broadened to include forecasting more detailed, micro elements of the demand for goods and services from socio-geographic and microeconomic behavior patterns of consumers. Data-driven demand forecasting of the right amount of the right product in the right place at the right time and at the right price is one of the underpinnings of a **demand management** practice in the supply chain.

The starting point for the forecasting process is to identify all the things that are needed to put a forecast together. These are inputs. Typical inputs include finding sources of **data** about the item to be forecast; obtaining information about external conditions, that is, about factors in the environment influencing a forecast; determining the needs of the user of the forecast; gathering the human and financial resources required to produce a forecast; and listing projection techniques. These are inputs not only to the forecasting process but also to the forecaster's judgment, which is applied throughout the process. The forecasting process also requires knowledge about the outputs of the process: formatting the output of the final product, presenting the forecast to the forecast users, and evaluating forecast errors on an ongoing basis.

# The forecast user will generally specify the format of the forecast output and collaborate with the forecaster about the kinds of analyses and/or variables that should be considered.

Once forecasting needs have been identified, a data-gathering network capable of continuously providing pertinent information about market conditions must be established. The data that have been gathered are then placed into some form of a relational database or **forecast decision support platform** (FDSP) for ease of analysis (to be discussed in Chapter 13). Data gathering and analysis can be very time-consuming and should both precede and follow the production of the forecast.

The end product of the forecasting process is clearly the forecast itself. A forecast should not be considered permanent or never changing. The dynamic nature of any market (i.e., consumer demands for goods and services) dictates that the forecasting process be revisable and repeatable at some future time. Because the value of any forecast is based on the degree to which it can provide advice in a decision-making process, the view of a market and its demands on a company within that marketplace (as expressed in terms of a forecast) must be current to be credible. In the next section, we describe the demand forecasting process as an integral part of a supply chain.

## The Role of Demand Forecasting in a Consumer Data-Driven Supply Chain

Traditionally, much of the responsibility for forecasting in corporations resided with sales forecasters. After all, they are closest to knowing what customer needs are. However, that role prescribed a process of determining what the business is expected to sell, based on what it could produce. The role of the sales forecaster represents an internally driven "push" paradigm of the traditional supply chain.

In a **traditional** supply chain, product flows sequentially through a system from one level to another (Figure 1.1) in a linear fashion. Driven by manufacturers and suppliers, the traditional supply chain is the furthest away from the ultimate consumer or end user. Each operating unit tends to maintain its own forecast information system (mostly in spreadsheets) and communication flows that occur between individual departments (referred to as silos).

In a new world dominated by global economics, the term supply chain has taken on a broader meaning. The Council of Supply Chain Management Professionals (CSCMP) (*http://cscmp.org*) defines a supply chain as the "material and informational interchanges in the logistical process stretching from acquisition of raw materials to delivery of finished products to the end user. All vendors, service providers and customers are links in the supply chain." This definition is a mouthful, but it underlies the recognition that competition is no longer limited to individual companies vying against each other.

A traditional supply chain is any sequential set of business operations leading from raw material through conversion processes, storage, distribution, and delivery to an end customer or consumer. In the demand-driven supply chain, demand information flows in the reverse direction as well.

In today's **consumer data-driven** supply chain, information in the form of orders and consumer needs also flows back in the opposite direction, so that all operations have complete visibility to the whole supply process (Figure 1.2). Instead of being driven or supplied by the manufacturer, consumers are the drivers of demand, demanding ever-faster delivery of cheaper, higher-quality products. Businesses success requires combining an integrated supply chain and a sound infrastructure with a focus on consumers.

In the context of an externally-driven *pull* paradigm of a supply chain, a demand forecaster is in the business of making detailed statements about future demand for products and services in the face of uncertainty. Demand forecasting and planning is the process that drives inventory levels to improve a company's ability to replenish or fulfill product to meet customer (and ultimate consumer) needs in a timely and cost-effective way. If forecasting does not have a good link to drive inventory stocks, improving it won't necessarily improve customer service levels or reduce costs.

A demand forecast is not just a number, outcome or task. It is part of an ongoing process directly affecting sales, marketing, inventory, production and all other aspects of the modern supply chain (Figure 1.3).

In the pull supply chain paradigm, demand planners and managers should start by reviewing an independently derived, unbiased baseline demand forecast, instead of first focusing on the targets that planners hope will result from a sales forecast, as in the *push* paradigm (Figure 1.4).



Figure 1.1 Traditional supply chain: Sell what you can make.



Figure 1.2 Traditional vs. consumer data-driven supply chains: Sell what you can make sell versus make what you can sell.



Figure 1.3 Operational impact of poor forecasts in the supply chain (courtesy Simon Conradie – Noetics Consulting).



Figure 1.4 A paradigm shift: Traditional SC (Sell What You Can Make) versus consumer-data driven SC (Make What You Can Sell). (*Source*: Larry Lapide (MIT))

# An effective forecaster can start with a simple demand theory without having to build complex models.

Demand managers must then reconcile their planning approaches with the assumptions for the future so that the most credible methodology will produce accurate and reliable forecasts. The Demand Management (DM) process makes use of computerized intelligence to synchronize and optimize essential elements of manufacture and distribution.

Demand planners and managers use item-level (disaggregated) forecast data from a number of sources to create a clear view of what product demand is likely to be, and then link inventory and replenishment processes to that future view. This bottom up demand forecast incorporates a logical and coherent series of steps that, if performed in a consistent, management-supported fashion, can improve forecasting effectiveness, reliability and credibility throughout the supply chain (Figure 1.5).



Figure 1.5 Financial impact of poor forecasts in the supply chain (courtesy Simon Conradie – Noetics Consulting).

Demand management (DM) refers to getting the right amount of the right product to where it is needed, while managing unproductive inventory levels to achieve maximum return on assets.

# Is Demand Forecasting Worthwhile?

The process of demand forecasting is not an exact science; it is more like an art form. As with any worthwhile art form, the forecasting process is definitive and systematic and is supported by a set of special tools and techniques that are dependent upon human informed judgment and experience.

An effective demand forecaster can develop a simple demand theory without having to build complex models. For example, you may be required to project the sales of a product or service per household. A total sales forecast can be obtained by multiplying the forecast of this ratio by an independent forecast of the number of households. In this way, an important relationship can be modeled that uses relatively simple methods. This gives a first approximation, which can provide valuable and timely information to decision-makers.

The demand forecaster is an **advisor**. The completed forecast must meet the requirements of the end user in terms of timeliness, format, methodology, and presentation. In the forecaster end-user relationship, the end-user has **domain expertise** about the environment surrounding the problem and variables that should be considered. The forecaster is knowledgeable about the forecasting process and specific forecasting techniques and models most appropriate for the problem. In most multi-national firms, the volume and complexity of required forecasts is usually sufficient to support a well-trained, professional demand forecasting staff.

#### The demand forecaster is an advisor, not just a producer of numbers.

## Who Are the End Users of Demand Forecasts in the Supply Chain?

The diversity of business activities creates work for many kinds of planners, or end users of forecasts; each with a special set of problems. The problems may be viewed in terms of a business's function and a time horizon for that function.

- **Executive managers** are concerned with current performance but even more concerned with future direction strategic planning. In which markets should the business operate over the next five to 30 years? An executive manager must identify and analyze key trends and forces that may affect the formulation and execution of strategies, including economic trends, technological developments, regulatory climates, market conditions, and assessment of potential competitors.
- **Financial managers** are concerned with financial planning, for which they need short-term (one to three months), medium-term (up to 24 months), and long-term (more than two years) forecasts. For example, cash flow projections are needed to negotiate lines of credit in the short term and estimates for capital investment for planning in the long term (Figure 1.5).
- Sales and marketing managers are concerned with short- and long-term forecasts of demand of
  products and services. Forecasting techniques suited to products and services have existed for
  some time. In forecasting a *new* product or service, these techniques are applicable if analogous
  products exist or if careful market trials can be conducted. The demand for the product can then
  be related to the economic or demographic profiles of the population in the market areas. These
  relationships can then be used to predict the product's acceptance and profitability in other areas
  having their own economic and demographic characteristics.
- Planners of competitive strategies use forecasting techniques to forecast the total market for example, total gasoline consumption, passenger-miles of traffic between cities, automobile purchases by size (sedan, compact, subcompact), computer storage requirements. Given the total market, each firm within it will then estimate its market share on the basis of product differences, price, advertising, quality of service, market coverage (including the size of the sales force), geography, and other factors specific to the market for the product or service. In many cases, market share is also estimated by using quantitative modeling approaches.

Production and inventory managers are often concerned with very short-term forecasts (hours, days, weeks). Production managers use forecasts to plan raw material and capacity requirements and schedule resources for manufacturing. In inventory management, exponential smoothing models find extensive application. (This important technique is like a weighted moving average, in which the most current data are given the greatest weight.) For extremely complex inventory systems, these models can produce many forecasts with varying degrees of uncertainty, which are closely monitored for unusual deviations between estimated and actual inventories. Sometimes deviations can be interpreted as event-driven and can be modeled to alter demand projections. Large deviations are flagged as exceptions, for future scrutiny and reevaluation of the forecast-generating model.

# Learning from Industry Examples

Throughout this book, we will examine practical forecasting problems from the author's broad experience as a practitioner in industry, consultant to forecasting organizations, and instructor to managers and students interested in learning about demand forecasting. Where appropriate, we also use time series (historical data about changes through time) from real-world sources to illustrate forecasting techniques and models and to compare or contrast results.

A time series is a set of chronologically ordered values of historical data, such as the sales revenue received by month, units shipped by week, or energy consumed per hour or day for an extended period.

The forecasting problems, borrowed from industrial experience, arise from the requirement for accurate, timely, and reliable forecasts of demand, sales revenues, product shipments, and services; throughout we develop forecasts of these items from actual data under realistic assumptions.



Figure 1.6 Sales-revenue forecasting example for telecommunications.

The telecommunications industry illustrates a number of considerations common to many marketbased forecasting applications (Figure 1.6 top frames). The global market that generates business telecom revenues may be viewed, in part, as the number of business telephones from which calls can be made. Messages (calls) are regarded as the quantity of service rendered (or product sold). The correspondence between revenues and messages is not one-to-one because additional factors, such as the geographical location of the parties and duration of calls, cause variation in the revenue per message. In general, the overall state of the economy, as measured by an economic indicator such as nonfarm employment, is known to influence the demand for business telecom service (Figure 1.6 bottom frames).

## **Examples of Product Demand**

As an example of product demand, consider the market for selling books online or in bookstores. The college textbook publishing industry is a particularly challenging area for demand forecasters. College textbooks, like fashion products, are highly polished products. They require years of preparation and are geared for a very limited yet noncaptive market. Accurately forecasting the potential demand for each title seems crucial. To provide book publishers with some assistance in conceptualizing the role of demand forecasting in the textbook industry, it is useful to create a visual representation or model of the publishing industry (Figure 1.7, *left frame*).

In another example, the economic growth in China in recent years has created a rapidly growing middle class and city white-collar jobs. These expanding demographics have increased disposable incomes that help raise living standards. People seek food that is both high in protein and convenient to the consumer. Supermarket chains expand and establish more stores to meet the demand, resulting in the increase of the consumption for ready-to-eat packaged foods. A Consumer Packaged Goods (CPG) manufacturer supplies more and varied products, such as chicken, for the fast-foods (FMCG) market to fulfill the demand from consumers (Figure 1.7, *right frame*).



Figure 1.7 (left): Demand for e-books. (right): Demand for fast foods.

Demand forecasting for Sales and Operations planning (S&OP) drives marketing, sales, logistics, production, and financial plans to determine disaggregated production plans of product demand or services

Different measures of economic activity, such as interest rates, industrial production, the unemployment rate, gross domestic product (GDP), volume of imports versus exports, and inflation rates, have special significance in other industries to help determine the size of some market at a designated time and place.

The revenue-quantity relationship, in the most general sense, is similar to that encountered in forecasting revenues from passenger miles of transportation, mortgage commitments from housing starts, expenditures for goods and services purchased during tourism travel, tax revenues from retail sales, and revenues from barrels of crude oil after refining. In each instance, the revenue depends on the mix of the products sold or services provided. However, for financial planning purposes, accurate aggregate revenue forecasts can often be derived without the necessity of forecasting every product or product combination and multiplying that by a sales price.

The CPG industry provides a somewhat broader sales and operational (S&OP) forecasting application, in which inventory, bills of material, routings, lead times, and customer orders must be accurately forecasted in a timely way before schedules and plans can be effectively established. Sales and operational forecasting incorporates the business plan, sales plan, production plan, and marketing plans into one information source. Detailed demand forecasts are prepared as inputs for planning inventory, establishing customer service, and determining production loads. They must be created at a disaggregated level in order to account for the product and customer detail required for manufacturing operations.

In the retail industry, department store sales may be influenced by a number of regional economic variables such as the **consumer price index**, average weekly earnings, and the unemployment rate. Retailers may also feel that the number of shopping days between Thanksgiving and Christmas has a major impact on the Christmas holiday sales volume, so their needs tend to be expressed by accurate disaggregated unit forecasts. Likewise, the shifting Ramadan holiday period will impact sales volumes reported for the month the holiday occurs.

Market planning and forecasting at electric utilities require demand and energy models, where demand refers to the level of electricity consumption at a particular instant in time and place, and energy refers to the level of total use of electricity over a given period of time. Residential electricity consumption is highly influenced by weather, economic, and demographic factors. Weather influences are measured by heating degree-days and cooling degree-days. The economic factors used are price and disposable income, and the demographic influences include size and age of dwelling, age of family residents, number and type of electrical appliances, and type of space and water heating equipment.

Figure 1.8 depicts a broad visualization of a packaged goods producer (retailer sums to 92.6%). The manufacturer produces a product for export, direct sales to consumers, the government, and the military; and sales to an extensive network of retailers. A grocery wholesaler or co-op retailer might distribute the product to supermarkets, grocery stores, and warehouse stores. Other distributors sell the product to chain drug stores, discount mass merchandisers, and variety stores. The entities being forecast are often product groupings segmented by geography (sales region or market zone) and customer-specific categories (warehouses, channels, or accounts).







Source: ENR & IMSAD Research Report, Distribution Network and Channels in Building Materials Sector, 2011

Figure 1.9 Is a forecast just a number?



Figure 1.10 When a single forecast can lead to potentially different decisions.

### The Demand Planner's Dilemma: Is a Forecast Just a Number or Something More?

Consider the demand for building products—for Turkey in this example, or any other published forecast of a product or service around the world. You might find a forecast as depicted in Figure 1.9. The overall growth rate in 2010 is stated as 11.5%. For 2011–2015, it is projected to be 14.5%. The actual numbers are not of interest here. We want to focus on what was omitted. As stated, the implications are that this forecast is projected to have a precision of + or - 0%, either exactly right or totally wrong. This is not credible.

#### Credible forecasting means that you will never have to be certain.

So what would a credible forecast be? Why is it necessary to be able to quantify uncertainty for a forecast? Depending on decisions made based on the forecast, it should be apparent that the same

forecast number could also be (14.5%: + 1.5% or- 1.5%), or say (14.5%: + 1% or- 3%) as shown in Figure 1.10. These could have different implications as forecast advice for demand and supply chain planning. Thus, credible demand forecasts are incomplete without a stated measure of uncertainty. Yet the prevailing forecast question asked of demand planners by managers in supply chain organizations today is "What is the number?!!"



Tens of thousands of years ago, if you asked a group of tribe members and community leaders to raise their right hand if they believed the earth was flat, all hands would go up. **Still today**, some people would do so, but if you were to ask a group of supply chain planners and managers today whether they believe a forecast is just a number, most hands would go up also. What is wrong with this picture? Today most people would not raise their hand for a flat earth theory, but they do appear to believe that a forecast is just a number. A flat earth mindset in forecasting does prevail.

Imagine taking a long airplane trip between Chicago and Shanghai. On the cabin screens, you can follow your flight on the flat earth map in front of you. Following a best FLAT EARTH forecast of fuel needed would take you along a STRAIGHT LINE on this map. But, why does the pilot not follow your forecasted number of the quantity of fuel needed? The airplane appears to be flying a much 'longer' flight that is curved. How **accurate** would that appear to a flat-earth forecaster?

While we know a curvature dimension must be added to a flat earth model to be accurate, should demand planners and managers continue believing and behaving as if a demand **forecast is just a number**, ignoring the **uncertainty factor** as an essential **dimension of variability**?

UNCERTAINTY IS A CERTAIN FACTOR in demand forecasting and should not be ignored in a smarter forecasting process.

# **Creating a Structured Forecasting Process**

Suppose that you are responsible for making a forecast of the demand for a product or service in your company for use during the next few hours, days, weeks, months, quarters, or even years. How do you begin to plan your work? The specific operations for each stage of the forecasting process are diagrammed in a flowchart below. We emphasize the iterative nature of the forecasting process.

Note that each stage has a feedback loop, indicating the need to allow for time in the forecasting cycle to iterate back to the beginning of a stage, perhaps once or twice (at most). This is also a design criterion for implementing a forecast decision support platform (FDSP) (to be described in Chapter 13).

## The PEER Methodology: A Structured Demand Forecasting Process

Under PEER, the four key stages in which forecasting is done are preparation, execution, evaluation, and reconciliation.



**Preparation**. Of primary importance when we prepare a forecast is that better forecasts result when the proper process has been meticulously followed. At this stage, we try to identify and understand the context and data framework in which the forecast is to be developed.

**Execution**. Once the forecasting context and a data framework have been established, we can turn to the execution stage. A systematic execution of a forecasting methodology leads to a better understanding of the factors that influence demand for a product or service. The demand forecaster who has a good handle on demographic, economic, political, geo-location-specific, competitive, and pricing considerations will develop the necessary expertise to make the most credible forecasts of the demand for a company's products and services.

**Evaluation.** The forecasting cycle is typically an iterative process. Once the forecasting models are built, we still need to turn our attention to an evaluation stage before posting forecasts. How well have the models performed in the past? The process of forecasting focuses attention on evaluating forecasts and using the right methodology for a given forecast (for example, not using short-term methods for long-term forecasts)

**Reconciliation.** During the forecasting cycle, we could be making changes to the models, projections and assumptions behind our forecasts. But in the end we need to come up with a final forecast (embracing change and chance); essentially a set of assumptions and numbers on which the company can build its future plans. Instead of focusing on the plans they hope will result from a forecast, forecast managers and users must reconcile their planning approaches so that the most credible methodology will produce accurate forecasts. Selecting the right forecasting methodology is the focus of Chapter 3.

Together these stages make up the PEER methodology.



# Case Example: A Consumer Electronics Company

# The Demand Forecaster's Role

GLOBL (a fictitious company) is one of the leading international providers of consumer technology products to a broad range of worldwide customers. GLOBL's mission is to provide

- development, manufacturing, and sales of educational technology products
- development and sales of hardware and software systems to support these products
- a broad range of customer-support services ranging from demonstrations, training, consulting, and ongoing maintenance.

You have just been hired by GLOBL as a demand forecaster. You have received some on-site training and have visited various overseas offices to learn about the scope of the job, which is extensive. Your responsibilities are to provide forecasting services to all GLOBL business units. You must appropriately serve all aspects of GLOBL businesses, including planning for demand and supply, marketing, sales and operations, finance, new product development and introduction, and corporate strategy.

Your manager has observed that, as with any business function, there are not nearly enough forecasting resources to address all the potential needs at GLOBL. Thus, careful evaluation and prioritization of forecasting work activities must be done. Also, there is a great opportunity to become more agile by better synchronizing some of the forecasting services now separately performed for each GLOBL business area.

Your initial assignment is to the demand/supply planning area of GLOBL, and your first product forecasting responsibility is a set of high-tech consumer products. However, over the first five years in their careers, it is usual in GLOBL for forecasters to be rotated through several diverse product and services assignments—as well as different aspects of particular business areas.



Your job description as a demand forecaster includes

- forecasting the demand for a group of GLOBL's products
- providing regular coordinated communications with the development, sales, and marketing groups
- developing reliable modeling approaches to predict sales volumes providing periodic, objective, and credible forecasts to the sales and operations planning (S&OP) process, which will use this forecast for production and capacity planning over the subsequent six months
- providing monthly forecast updates and related information for revenue planning
- presenting and defending forecasts to senior management, as required
- reviewing forecasting performance on an ongoing basis with your user groups and information sources to identify areas needing improvement

# PEER Step 1: PREPARE by Identifying Factors Likely to Affect Changes in Demand

The first two activities of the Preparation phase involve defining the parameters that will govern the forecast and making first choices among alternative factors or **drivers of demand**. First, the forecaster identifies the forecast users and their information needs. For example, revenue forecasts are needed by a business to determine the expected net income and return on investment for a base case. You want to be certain that you have an understanding of which products or services should be measured in your forecast. These considerations help the forecaster answer the question: Can cost-effective, timely and agile forecasts be provided to assist planners or managers in making their decisions?

Next, a forecaster's own practical needs must be recognized; if they are overlooked, the credibility of the forecast will be diminished. So you should consider your time, administrative support needed, expenses for computerized forecast production, and costs related to field visits.

A demand forecaster also needs information about the business environment in which a company operates: Which factors have affected the demand for a product or service in the past and are likely to affect the demand in the future?

For example, in the consumer goods industry, the demand for a product is forecast along with a measure of the effect (**price elasticity**) a change in price of a product will have on its demand. Or the demand forecaster may need to consider demographic, economic, and market factors: factors such as income, market potential, and fashion and consumer habits are usually an integral part of a formal



demand theory:

• *Income* measures a consumer's ability to pay for a company's goods or services. The price of its goods or services and the prices of its competitors' are certainly important.

• The *market potential* represents the total market for products or services being forecast. This might be the number of households or business establishments.

• Fashion and consumer habit are crucial because innovation and change create new products and services, thus causing people's tastes and habits to change. These changes must be monitored. For example, the introduction of air transportation caused people to change travel habits; the resulting impact on the railroad industry was tremendous. Also, the introduction of computers and smart phones has impacted people's work habits.

# The GLOBL Product Lines

Although GLOBL develops, manufactures, and sells a broad range of consumer products, you have three product lines, or families of products, for which you will develop forecasts (Figure 1.11):

- Product line A is a family of consumer products for early childhood development. The consumers for these products are preschool children in the autism spectrum. Their needs are for educational toys, games, and devices that allow them to better adapt to their environment and enhance their growth potential within the community.
- Product line B is a family of consumer products for academia and institutions of higher learning. The consumers for these products are students requiring specialized learning devices and educational materials to allow them to cope more effectively and competitively in a general academic environment.
- Product line C is a family of consumer products for the occupationally challenged. The consumers
  for these products are adults in the workforce requiring customized aids for enhancing their
  productivity in the workplace.

### Product Lines

• *iFunBuddy* is a tablet designed for children with autism preloaded with specialized developmental and learning apps



- iHearBuddy is a tablet provides university students with disabilities a learning aid such as translating lectures
- iWorkBuddy caters for specialized needs of the workforce with disabilities



Figure 1.11 "i-Buddy" product line for GLOBL— iFunBuddy, iHearBuddy, and iWorkBuddy.

# The Marketplace for GLOBL Products

There are five major players in the worldwide educational technology marketplace, plus another dozen niche players. GLOBL has a centralized market intelligence staff that is responsible for overall marketplace trends and outlooks, keeping track of competitive activities and market share, and performing specialized marketplace studies as required by sales, marketing, and product development.

• **GLOBL Product Development**. GLOBL does all the development work on the three product lines you will be forecasting. This means that GLOBL maintains a development staff whose responsibilities include evaluating and tracking customer requirements for educational products, determining and prioritizing what needs may be best pursued by GLOBL, designing and developing products to meet these needs, determining go-to-market strategies for these products, tracking

GLOBL product performance versus objectives, and enhancing products required to meet GLOBL objectives.

- GLOBL Sales Force and Channel Strategy. GLOBL has a worldwide team of dedicated product sales specialists. There are also a number of business partners who sell GLOBL products, often along with other products and services. There is a strong focus on increasing the use of web-based facilities to exploit e-business sales.
- **GLOBL Manufacturing**. GLOBL performs manufacturing activity for the products you forecast. Worldwide manufacturing supply/demand planning is performed centrally for all products, although there are several manufacturing sites for each product.



- GLOBL Product and Strategy Details
  - Product line A sells into the preschool market. In recent years, product line A has seen dramatically increased use to support Web-based applications.
  - Product line B sells into the academic market and institutions of higher learning. Although GLOBL has been in the market for quite a few decades, the original versions of this line were introduced just over 36 months ago. Sales have been normal for the past year. Two years ago, there was an unexpected upswing in demand in quarter 3, which caused big manufacturing problems. A dedicated sales force does over 90% of sales and has grown significantly in size over the past three years. There are currently plans for a further strengthening of the sales budget due to concern that GLOBL is still number three in this marketplace. This sales force operates off a quota system with sales contests scheduled approximately once a year, usually in the last quarter. Selling in this marketplace depends on establishing good relationships with the educational institutions. GLOBL's competitors appear to be more successful at this. You have difficulties getting solid information on the product line's sales activities from the sales force.
  - Product line C sells into the commercial workplace market. It spans a wide range of occupational functions in industry, supporting complex needs across many business applications. Product line C has seen modest growth over the past several years; new and esoteric applications in many commercial marketplaces are driving a niche market. GLOBL has divided its sales efforts between its own sales force and its business partners in roughly a 30-70 split. Good contacts with traditional customers have been key to sales success. However, forward-looking strategists are beginning to be concerned regarding the trends to mutual e-procurement initiatives in these customers.

In addition to these demand factors, supply considerations should also be taken into account. In forecasting regulated services (such as residential waste management or power utility in some areas), it is important to recognize that a corporate charter requires a company to serve consumer demand. Its management does not have the option of meeting only a part of the demand. In competitive industries, where this is not so, the demand forecaster and the forecast user must evaluate the interaction of demand and supply before arriving at the final forecast.

The problem-definition step concludes with a determination of the costs versus benefits of the alternative solutions. The forecaster must look for solutions in which the benefits exceed the costs. But has the forecaster been adequately prepared to measure costs and benefits?

# PEER Step 2: EXECUTE to Select a Forecasting Technique



Many different forecasting techniques are available ranging from elementary smoothing methods to time series and regression models. A forecasting model is a job aid for forecasters: it creates a simplified representation of reality. The forecaster tries to

include in the representation those factors that are critical and to exclude those that are not. This process of stripping away the non-essential and concentrating on the essential is like peeling an onion and is the essence of forecast modeling.

#### A forecasting technique is a simplified representation of reality for making projections.

Although abstract, models permit the forecaster to estimate the effects of important future events or trends. In the cable TV industry, for example, there are thousands of reasons why subscribers want their homes connected or disconnected for use of the Internet or to place calls over a digital network. It is beyond the scope of the forecaster to deal with all these reasons. Therefore, a forecaster attempts to distill these many influences down to a limited number of the most pertinent factors.

In a particular place, such as Detroit, Michigan, the forecasting model might look like Figure 1.12. This model assumes that the automobile industry creates jobs for people, who then buy homes or rent apartments and want cable services. The demand forecaster's job, for instance, is to determine the relationships among employment levels, household growth, land use, and cable service demand along with a quantification of uncertainty.

Mathematical equations are used to develop models that represent a real-world situation. For a cable TV service model, such an equation might take the form

CTV demand =  $b_0 + b_1$  (Employment) +  $b_2$  (Number of housing starts) + random error

where  $b_0$ ,  $b_1$ , and  $b_2$  are coefficients determined from historical data.



Figure 1.12 Forecasting mode of demand for residential CTV services in Detroit.

Models such as these simplify the analysis of some problems, but, of course, do not account for all the factors that cause people to behave as they do. Notice that the model summarized in the equation does not include information on the prices of other goods and services, but does include the uncertainty factor.

As another example, consider tourism demand forecasting. International tourism has grown very rapidly over the past few decades and has become a major part of the global trade. Tourism demand measures a visitor's use of a quantity of a good or service; such measures commonly found in tourism forecasting include number of visitors to a destination, number of transportation passengers, and amount of tourism expenditures. Some factors that are known to affect tourism demand include personal disposable income, travel costs, natural and human-made disasters, and weather (Figure 1.13, *top*).

To get a measure of the nature of demand variability and uncertainty, Figure 1.13 (*bottom*) shows that the total variability in the data (as determined from a preliminary ANOVA decomposition technique, explained later) is comprised of 86.6 % seasonality, 12.1 % trend and 1.3% irregular (unknown, other than trend/seasonal effect). The primary driver, in this example, is seasonality, so as we'll see a model with a seasonal-trend **forecast profile** (e.g. Holt-Winters, to be discussed in Chapter 8, or the ARIMA (011) (011)<sub>12</sub> "airline" model, to be discussed in Chapter 9) should be on top of the list of techniques to be considered.

Forecasters need to understand the factors driving consumer demand and consumer trends in their areas in order to create a demand forecast for a product or service. What other factors of demand or domain knowledge might you need to quantify the remaining irregular variation?

Modeling and projection techniques are tangible and structured, just like the forecasting process. A credible modeling approach should be able to produce uncertainty measurement and reproducible results. As the analytical engine of a forecasting model, these techniques provide the basis for understanding **forecast profiles** and **forecast error** impacts (Forecast error is conventionally defined as Actual–Forecast). Models perform similar tasks regardless of the data they use; although some inputs to the forecasting process depend on the context of the given situation, projection techniques do not. For this reason, the forecaster must exercise sound judgment in selecting and using the projection techniques that yield the credible **forecast profiles**. Through a systematic process of elimination, the forecaster can identify those projection techniques that will provide the greatest reliability in the development of the forecast output.



Figure 1.13 Time plot (*top*) and exploratory ANOVA trend-seasonal decomposition pie chart (*bottom*) of monthly tourism demand in a metropolitan area. (*Data source*: D. C. Frechtling, *Practical Tourism Forecasting* [1996])

There is a trade-off between simplicity and completeness in every model-building effort. Multiequation causal models (Chapter 10) are commonly used to approximate the relationships between retail consumption and its drivers: price, advertising spending, coupons, competitive influences and seasonality.

Because seasonality is such a dominant factor, the data are often seasonally adjusted first before modeling begins (Figure 1.14). On the premise that there is a strong relationship between consumer purchases and factory shipments, a related causal model around factory shipments would include among its drivers retail consumption, merchandising, trade allowances, and promotional lift variables.



Figure 1.14 Time plot of monthly retail sales, adjusted for seasonal variations, trading-day, and holiday differences. *Source:* (https://www.census.gov/retail/marts/www/download/text/adv44000.txt)

A forecasting technique selection is a systematic procedure for producing and analysing forecasts.

In this book, we analyze and forecast variables by emphasizing **exploratory data analysis** (EDA) for assuring data quality and basic forecasting techniques for generating credible and reliable forecasting profiles. We begin the analysis with traditional approaches and supplement them with **resistant** (those that safeguard against unusual values, like outliers) and **robust** (those that safeguard against departures from classical normality modeling assumptions) alternatives to the same problem. More advanced techniques, including the autoregressive, integrated, moving average (ARIMA) models, based on the BoxJenkins methodology, dynamic regression and some econometric modeling with multiple variables and equations, will be considered as well.

#### There are numerous alternative ways of generating any forecast.

# PEER Step 3: EVALUATE Forecasting Models

With a data framework in place to process, analyze and manage data, the demand forecaster completes

the forecast techniques selection step. Next, the forecaster starts to create forecasts with each selected method. After executing the forecast modeling step, the demand forecaster evaluates each technique. The forecast model evaluation step is called **diagnostic checking** and often results in modifications of the initial models until acceptable models are obtained. This phase involves accuracy measurement based on forecast error analysis (to be discussed in Chapter 4).



# PEER Step 4: RECONCILE Final Forecasts

After completing the evaluation of forecasting models (to be discussed in Chapter 11),

- informed judgment, important throughout the process, is used to create forecast adjustments and select the forecast values and uncertainty ranges from among the possible candidates
- estimates are made about the reliability of the forecast in terms of prediction limits, and presentations are made to gain the acceptance of the forecast
- the forecasts are monitored to ensure their continuing relevance, and forecast changes are proposed when necessary

# Getting INSIGHTS into Forecasting New Demand for Products and Services

One objective of a smarter forecasting process is to identify and evaluate systematically all factors, which are most likely to affect the course of demand for products and services. What can we do for *new* demand for which there are no historical patterns? The demand forecaster should identify *measurable* variables for factors affecting the quantity demanded for a market or region of interest, using comparable products or services for which there are historical data

Figure 1.15 is a **predictive visualization** of a GLOBL product line B product called iHearBuddy (a learning aid for foreign language students that translates lectures). The plot shows historical data values, a trend/seasonal forecast profile with prediction limits based on the Additive Holt-Winters model, coded ETS (A,A,A); see Chapter 8 for detaks. It clearly shows a dominant seasonal pattern (reflecting *consumer habits*?) and a less pronounced trend pattern (reflecting *consumer demographics*?).



Figure 1.15 Predictive visualization of IHearBuddy product demand: monthly time series of a seasonal product in GLOBL product line B, showing history, forecast profile (change), prediction limits (chance), and moving average smoothing of history and forecasts.

In Figure 1.16, the three ETS components are displayed as pie- and cone charts to visualize the relative contribution of the trend and seasonal variation to the total variation. Using an exploratory year-month decomposition method, calculated with the "Two-way ANOVA Without Replication" routine in the Excel Data Analysis add-in (described in Chapter 8), we can make the interpretation that the data made up of 51% Seasonality, 4% Trend, and 45% Other.

Based on the forecaster's domain knowledge and the recent history of product *i*HearBuddy, the forecaster may be able to advise that if the business can capture 7% of the educational market, it will yield a monthly internal rate of return of 21.5%. The business planners have designed the daily production requirements, equipment, manpower, and facility requirements based on these sales targets. Recent recessionary trends have been a concern, and now the planners would like to backtrack and see what the outlook of the consumer electronics industry is before embarking on the new venture.

The information on the industry would indicate whether this product is still a wise investment. The demand factors and consumption trends that need to be investigated include price, income, demographics, advertising, and regulation.

As an exploratory step, the demand forecaster could make some insightful assumptions for product line B. The dominant seasonality can be quantified by consumer habit factors, such as number of holidays and School openings/closings, driving the demand for Product Line B. The trend relates to the underlying growth of the student population and can be quantified by the age-cohorts of student consumers, for example.



Figure 1.16 Pie chart and cone chart as alternative ways to depict total variation in the demand variable in terms of (1) seasonality (51%), (2) trend (4%), and (3) other (45%). Exploratory decomposition display of GLOBL product iHearBuddy created with Excel Data Analysis add-in for two-way ANOVA without Replication.

The "Other" component (45%) still contains information about everything else not attributable to consumer habits (seasonality) and consumer demographics (trend). This could include promotions, economic cycle, unusual events and random error. In a modeling environment, we first characterize the trend/seasonality with a time series forecasting model with a trend/seasonal forecast profile (e.g. Holt-Winters exponential smoothing or an ARIMA (011) (011)<sub>12</sub> "airline" model; these are in the same family of the State Space Forecasting models discussed in Chapters 8 and 9, and incorporated in the PEERForecaster, a license free Excel add-in downloadable from *www.peerforecaster.com*.)

The model residuals (Actual minus Fit) are analyzed and used to quantify the remaining factors with causal (regression) models, for example. This iterative process is like peeling an onion to uncover *change* and *chance*. The models give insight into the appropriate forecast profile (*change*) while forecast errors (Actual minus Forecast) from holdout samples can be used to get insight into the uncertainty factor (*chance*). In this sense, we characterize uncertainty as a *certain* factor.

The impact of the dominant drivers of demand can be summarized in a Factor Impact Matrix (Figure 1.17), along with a predictive visualization of the historical and future impact of a driver of demand (Figure 1.18). To monitor a time history for the impact of drivers on demand on an ongoing basis, we create factor matrices for the Immediate Past, Present and Future. The time periods should be representative of the current context or situation. For example, one could use lead-times for inventory or production.

Oveall I	mpact
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Factor	Past changes	Current impact	Change in upcoming periods	Max. influence that the factor can have (+/- %)
Economy	+ 3%	- 1%	- 5%	+/- 10%
Demographics	+ 2%	+ 2%	+1%	+/- 3%
Price Index re Competition	- 4%	- 4%	- 6%	+/- 8%
Income	+ 8%	+ 6%	- 3%	+/- 16%
Advertising	- 2%	- 8%	+ 2%	+/- 8%

Impact in the Peri	od	Current	Future
Factor	Direction (+/-)	Intensity (1-5) 1 = Low	Intensity (1-5) 1 = Low
Economy	+	1	1
Demographics	+	4	2
Price Index re Competition		3	3
Income	+	2	5
Advertising	+	5	4

Figure 1.17 Illustrative factor matrices for trend and seasonal drivers of demand for GLOBL product line B.

The direction would indicate the impact a factor would have on demand if it were increasing or decreasing. For example, price increases would tend to result in decreases (-) in demand, while increases in holidays and festivals would tend to increase (+) the demand for electronics products. The quantification of the resulting impact is based on informed judgment and domain expertise and signifies the intensity on a numerical scale, say 1 to 5.

#### The The factor's The overall impact The expected historical effect on future impact of of the top factors impact of a projected a factor on demand in the factor over demand the past few current period periods

#### The Impact of the Best Factors

#### Proportion to circle area

Intensity	Rad	ius (x2)
	1	1
	2	1.414213562
	3	1.732050808
	4	2
	5	2.236067977

#### Figure 1.18 A predictive visualization of the impact of a driver of demand.

To summarize the impact of a driver on demand, we create a **predictive visualization** of the driver or factor by relating the score to the size of a dartboard surface. Use the relationship of Area =  $\pi$  (radius)<sup>2</sup> to determine the size of the circles shown in Figure 1.19. For instance, for a score of 5, the circle should appear five times larger than the one with a score of 1. To get the correct visual effect, you can accomplish this as follows: Score 1  $\rightarrow$  radius 1, Score 2  $\rightarrow$  radius V 2. Score 3  $\rightarrow$  radius V 3, Score 4  $\rightarrow$  radius 2 and Score 5  $\rightarrow$  V 5. If you have deeper domain knowledge, you can extend the scale to 7 or 11.

#### Uncertainty is a certain factor in characterizing change and chance.

#### Takeaways

- Demand forecasting is a structured process that produces a specific output, namely advice about the future. Because the future is not completely predictable, the systematic structure of a smarter forecasting process establishes the foundation on which the most important ingredient (human judgment and intuition) is based.
- The purpose of a smarter forecasting process is to identify and evaluate systematically all factors, which are most likely to affect the course of demand. At first glance, such a process may seem inefficient and interminable; but in practice, you will discover that a reasonable course will often become apparent, especially with experience.
- Problem definition is probably the most critical phase of any forecasting project. It is necessary at this stage to define what is to be done, design a data framework and establish the criteria for successful completion of the project or forecast. The four **PEER** phases of the smarter forecasting process are independent of the item to be forecast and the input parameters. It is essential to agree on the required outputs, time, and money to be devoted to solving a problem, the resources that will be made available, the time when an answer is required, and, in view of these, the level of accuracy that may be achievable.
- Exploratory data analysis, forecasting, and model-building should only begin after these kinds of agreements have been reached. If the prospects for reasonably accurate, credible and defensible forecasts are good, the forecaster proceeds to the next step of the process.

- Lastly, demand forecasting is a complex process. Complex processes require checklists for effective execution.
- A comprehensive checklist for general forecasting can be found at Forecasting Principles (http://www.forecastingprinciples.com/), a site devoted to summarizing useful knowledge about forecasting that can be used by researchers, practitioners, and educators. A checklist is good advice because it appears to be broadly applicable to all forecasting functions.



#### A properly trained forecaster is one who does the right things in the correct sequence.

The following is a checklist of forecasting principles created for demand forecasters and planners of global health products; this checklist is clearly more generally applicable.

Source: http://www.cgdev.org/doc/ghprn/Demand\_Forecasting\_Principles,Sept-06.pdf

- ✓ Have I identified the principal customers/decision-makers of the forecast and do I clearly understand their needs?
- ✓ Have I understood and clearly communicated the purpose of the forecast and the decisions that will be affected by the forecast?
- ✓ Have I created a forecasting process that is independent of plans and targets?
- ✓ Have I understood the political considerations and taken measures to protect the process from political interference? Is my process transparent?
- ✓ Have I understood the broader environment in which the forecasting process is occurring?
- ✓ Have I created the forecast in the context of market and policy trends, portfolio of investments, and new product developments by suppliers? Have I clearly communicated this context?
- ✓ Have I created a dynamic forecasting process that incorporates and will reflect changes in the market and in public policy as they occur?
- ✓ Have I selected the techniques that are most appropriate for the forecast problem and data available? Do I understand how to apply the various techniques that are most suitable? Have I obtained decision-makers' agreement on the techniques?
- ✓ Does my methodology reflect the appropriate level of accuracy and detail that is needed for the forecast? Have I explicitly identified prediction intervals in the forecast?
- ✓ Have I made my forecast assumptions clear and explicitly defined them for those who will use the forecast? Do I understand the data and their limitations? Have I searched for data from multiple sources and gathered both qualitative and quantitative data? Am I using these different types of data appropriately?

