Independent Analytical Research

Demand Forecasting, Resource Planning and Procurement Strategy: Review and Sample Case

White Paper

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Preliminary

"A good hockey player plays where the puck is.
A great player plays where the puck is going to be…"
Wayne Gretzky

The pace of change occurring in markets after the last world economic crisis requires new business approaches and methodologies, which would reflect current and future market tendencies, and would form the basis for the growth of companies that actively utilize them. The last recession clearly demonstrated that application of innovative and scientific methodologies in business operations result in unabated development, while the "business as usual" approach either causes dramatic decrease in revenue and profit or forces operators to leave their markets. Such losses are more typical for businesses that focus mostly on 'here and now' while overlooking long-term strategic development or operational optimization.

The purpose of this white paper is to enable beginner forecasters and resource planners to make first steps in the right direction by supplying them with approaches that will help to anticipate and proactively react to the market trends and customer demand. Doing this right will improve business operations that will further bring cost savings, more growth and profitability. To achieve these goals, certain business practices need to be revised and improved. In particular, Strategic Demand Forecasting, Resource Planning and related procedures, as being extremely important operational assets for a vast majority of sales and services companies. We will also review methodologies that can support further development of resource planning, supply chain, budgeting and other related operations. Specifically, we will:

- consider various forecasting methodologies and their applicability in relation to historical data set conditions and forecasting horizon;

- examine Time-Series statistical methodological approach, as well as its use for business forecasting;

- go through the business case that demonstrates advantages of the multi-methodological approach in business forecasting;

- review budgeting, pricing and product segmentation issues and their relation to the general business efficiency improvement.

The methodologies described below are based on many years of academic research of the topic, as well as on numerous successful developments and implementations of the considered technologies in business processes of mid- and large-scale enterprises and government institutions.

Problem Description

Common Case

Mistakes are an unfortunate inevitability in business activity. And one of the most common and quite costlier problems that any sales or service company may face is an unbalanced stock inventory (or wrong capacity in case of service providing). The matter is that companies invest most of their money into the inventory and/or service capacity, and even tiny resource planning error may affect a lot to the ROI, revenue and profitability.

This may often be a result of an inaccurate resource management strategy in general and highly subjectively personalized procurement approach in particular. The latter reflects a situation when a purchaser or a planner makes a decision based solely on intuition and his own understanding of the market situation, or at best, applies the most basic forecasting methods for demand anticipation and resource planning. Sufficient knowledge of the market and personal business acumen may help the operations to run smoothly initially. However, as markets change and the product volume and number of customers increase, errors will appear. In this scenario the total monetary value of the inventory may greatly exceed that of the sales volume, while inventory turnover drops down, and the number of low-demand items and pent-up demand go up dramatically. Eventually these problems will penetrate into other departments like sales, manufacturing, financial and others. The latter affects procurement through incorrect budgeting - and the cycle would repeat itself. If sales or services are not highly seasonal, the stock or planned capacity may be realized soon. Otherwise, the dead stock or redundant service capacity might wait for the next peak season that is resulting in huge irrevocable expenses.

An efficient cure for such situation is application of more appropriate methodologies and business techniques to run the operations – demand forecasting and resource planning in particular.

In general, any operational improvement is based on a triad of Methodologies, Tools & People. Business development will suffer if any of these parts is missing. However the combined efforts of all the elements – precise, powerful and sophisticated Methodologies implemented into easy-to-use Tools, operated by qualified People – greatly affects business growth. This white paper is dedicated to the first component of the triad – Methodologies.

Forecasting Focus Point

The main point of forecasting is to support a company acting proactively in customer demand anticipation. More specifically, the goal of forecasting is to determine, analyze and estimate a probable future customer demand in order to enable a company to bring its capacity on par with it. That allows goods and service providers to meet their customers' needs at minimal cost.

From the monetary standpoint, resource planning, and demand forecasting as a part of it, is very important and useful business tool. Comparatively small investment into improvement of resource planning results in huge saving for the company in total. The author's observations indicate that some 10% of the forecasting improvements may result in up to 30% of the company's saving annually, while forecasting improvement costs are simply negligible compared to the total annual cost savings. The reason is that accurate goods purchase and distribution lead to faster turnover, savings on warehousing and transportation, reduced pent-up demand, higher customers' loyalty, which finally result in greatly increased revenue and profit. Thus, right forecasting and resourcing are instrumental for continuous business success.

In order to research that, we will briefly outline related theoretical approaches and consider some sample cases that could-be further applied to a wide variety of demand planning strategies. The below provided approach earned its reputation as an effective and powerful forecasting and resource planning tool, which results in huge cost saving for businesses.

Methodological Approach

Forecasting and Planning Horizons

Before committing to any forecast, a relevant and precise time-frame (planning horizon) should be outlined for the purpose of goal-setting. Planning horizons should be based on a current corporate strategy, long- and short-term plans, amount and quality of dataset required for forecasting, and other related conditions. Only when all these are available, it becomes reasonable to set planning horizons that are in line with the business requirements. The lack and/or inaccuracy of any of the above may lead to the forecaster's wrong assumptions that ultimately result in a wrong forecast.

Corporative political considerations may affect planning and forecasting decisions dramatically, creating systematic biases. An incorrect planning horizon assumption is often driven by an upper manager's decision, which subordinate forecasters have to comply, thus compromising accuracy of forecasting. Alternatively, when there is poor inter-department communication or coordination, each department may define its planning horizon differently, causing further confusing. To avoid that, each company has to decide upon and uniformly formalize terms and metrics as dictated by the current and future business requirements – e.g. "short- /mid- /long-term" meaning "X to Y" hours/days/weeks/months, etc. Also, all departments should coordinate their forecasting activities and act uniformly in order to make forecasting methodologies option understandable, transparent and acceptable for all involved parties.

Development of the formal rules and definitions is a common challenge for the vast majority of businesses, but creation and maintaining of such "bureaucracy" is imperative for proper resource planning. In fact, uncertainty and complexity are the key causes of inadequate planning. And on the contrary, predictability, stability and a clear set of easily comprehensible rules in a business environment form the core for the growth in general business efficiency.

Methodological Overview

"Make everything as simple as possible, but not simpler"
Albert Einstein

Selecting a forecasting methodology that is most appropriate to the problem is critical to success, because picking a correct method in forecasting is similar to a drug choice in health industry. Get it right, and efficiency and productivity of the business rise dramatically. And similarly, the wrong or unsuitable method will impair the performance a lot. It should be thus noted, that the choice of particular forecasting methodologies becomes possible only after all common terms, metrics and rules are defined.

As observed, many rookie forecasters commonly tend to fall for a one-size-fits-all formula applied to a wide range of problems. Unfortunately, just like a cure-it-all magic pill, such formula, capable of producing reliable results for any imaginable problem, does not exist. So, the only way to do it right is to apply appropriate methods and techniques to each considered problem.

Below we are considering some most commonly used forecasting approaches that will exemplify why simple and cheap solutions may result in costly errors.

Figure 1 demonstrates approaches based on Moving Average (MA) and Quarterly Average (QA) forecasting methodologies applied to an artificial Demand sample.

The first method (MA) calculates next month's demand forecast as an average value of the three prior months, then the forecasted period is "moved" month by month over a year span (Figure 1: dash-line). This relatively simple method works well for markets with none or weak seasonality. However, its application to highly seasonal markets may result in big losses for a business as the seasonal peak months' forecasting values are based on off-peak low demand data, which results in a huge pent-up demand over there. While, high demand volumes of the three previous months create big over-supply situation during the off-seasonal periods. The latter also results in big losses for a business due to goods (and investment) turnover decreasing.

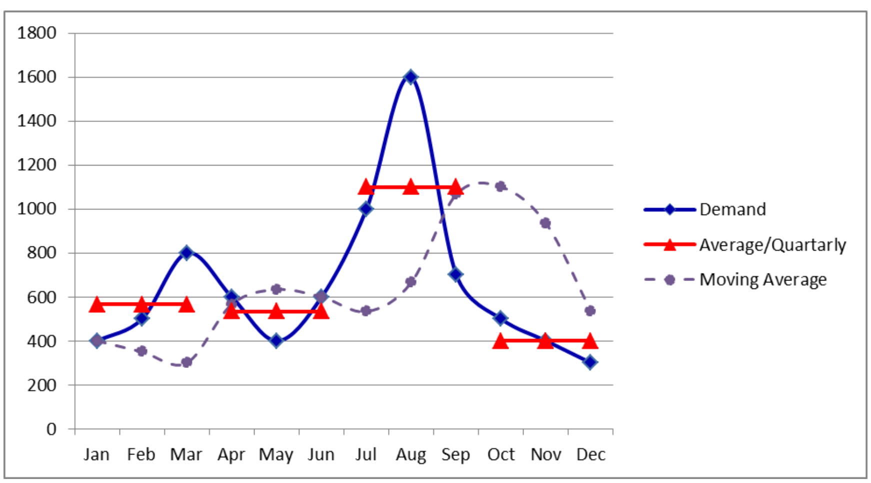

Figure 1. Sales Demand, and MA and QA Forecasting Approaches

A brief analysis of the data for the MA-forecasting case results in the following:

- Total annual demand for the considered sample case is 7,800 SKUs.

- Total annual stock surplus is 1967 SKUs. That means that around 35% of the purchasing investment are comprised of low-turnover stocks, and a company's ROI is decreased dramatically especially during the past four months.

- At the same time, annual pent-up demand is 2083 SKUs, that being especially painful in the peak seasons (Figure 1: March, July and August). That means the business earned approximately 36% less compared to what it could (*NB: purchase prices are used; in sales prices the pent-up demand is even higher*).

- Average turnover is around 1.4 month in this case. Assuming the average turnover should be 1.0 (a common business practice), the MA-based forecasting model tends to negatively affect the goods and investment turnover by 40%.

The Quarterly Average methodology applies the average value of a whole quarter equally to all months of the quarter (Figure 1: red lines). The method often applies last year's quarterly data to the current year forecasting. The approach is applicable in case of stable year-by-year seasonality and sales volumes. This method more accurately reflects seasonal fluctuations and generally provides better results compared to the MA-based approach. Yet it still decreases the total throughput (overstock around 15%; pent-up demand around 15%; annual turnover 1.2) and is barely adequate for markets with high volatility, as well as for growing and declining markets.

Therefore, the above MA- and QA-based forecasting methodologies may work fairly well for some particular cases, and might be occasionally applied. In reality however, many businesses overlook even these simple approaches when trying to narrow the gap between the market demand and their capacity. Based on the author's observations, the vast majority of businesses still conduct demand forecasting and resource planning reactively. "Key assumptions" and "expert knowledge", rather than proven scientific solutions, are utilized for resource planning, defying the operators a golden opportunity to dramatically cut their expenditures.

To summarize the above, oversimplified forecasting and resource planning approach, when a single forecasting and planning methodology is applied to varying problems, may cause substantial losses for a business. The only worse option is not using any forecasting methodology at all.

At the same time, it is impossible to apply an individual solution to each of the endless existing specter of problems, and therefore the most effective approach is seemed to put different problems through a filter of defined criteria and to arrange them into groups based on their similarity. Then it will be possible to pick the most appropriate method for each such group.

Table 1 provides taxonomy of the most commonly used forecasting methodologies. The author does not intend to scrutinize each method as they are well described in numerous publications, while would like to consider the time-series methodology that is feasible for a wide range of business applications. Before that though, we will briefly review methodologies (see Table 1) that are the most appropriate for strategic forecasting and resource planning operations.

Forecasting Methodologies		
Intuitive Methods	Individual Expert Estimations	Individual Survey
		Analitical Memorandums Method
		Scenario Planning Method
	Collective Expert Estimations	Collective Survey
		"Commission" Method
		Brainstorm
		Delphi Method
		Heuristic Forecasting Method
		Generation of Ideas Method
Formal Methods	Extrapolation Methods	Method of Trends
		Exponential Smoothing
		Probab. Modeling and Aadptive Smoothing
	System & Structural Methods	Method of Functional Hierarchy
		Method of Morphologic Analysis
		Matrix Method
		Network Simulation
		Structural Analogue Method
		Graphs and Tree of Objectives Method
		Scenario Forecasting Method
	Mathematical Methods	Regression and Correlation Analysis
		Group Method of Data Handling
		Factor Analysis
		Pattern Recognition Method
		Variational Methods
		Spectral Analysis
		Markov Chain Method
		Mathematical Logic
		Stationary Time Series Modeling
		Non-Stationary Time Series Modeling
	Associative Techniques	Imitation Modeling Method
		Historical & Logical Analysis
		Associative Pattern Recognition Method
		Artificial Neural Networks
		Data Intellectual Analysis
	Overcoming Methods	Forecasting Patent Method
		Importance of Invention Assessment
		Publications Flow Analysis

Table 1. Forecasting Methodologies

The following forecasting methodologies could be utilized to apply in mid- and long-term forecasting:

- Absence of historical data (e.g. brand new product) necessitates the forecast to be based on expert estimations and/or Method of Analogues through a historical data association of similar products;

- Limited historical data set (2 – 11 observations) leads to a mix of the expert estimations (Intuitive Methodologies) and simple trends (e.g. linear, exponential, logarithmic and similar);

- Extensive data set that reflects complete season (12 – 23 entry points) allows a forecaster to apply the simplest statistical methods (e.g. Running Average), while the above pointed approaches still remain suitable. In this particular case, the simplest statistical methodologies to expert estimations ratio should be roughly equal (50/50 or so) to balance biased expert estimate with historical tendencies and market conditions;

- Two to four complete seasons (24 – 48 observations) can provide comprehensive product history (sales or service), also allowing application of more sophisticated Mathematical Methods. A broader historical horizon (49+ data points) opens up yet more forecasting opportunities, but 3-4 complete seasons (36 – 48 entry points) are quite sufficient to comprehensively evaluate historical behavior of a product or a service, resulting in a high level of the forecasting accuracy.

The vast majority of businesses have sufficient available historical data, enabling them to utilize the last of the above options for their mid- and long-term planning operations. And for that reason we will elaborate on this most commonly used forecasting methodology, based on Time-Series data analysis.

Forecasting: Preprocessing

Accuracy and correctness of a historical data set is one of the basic elements of any future demand forecasting. More specifically, to anticipate any future market demand properly, a company has to account for a compound set of numbers for historical sales/services (that occurred in the past) as well as pent-up demand (that was supposed to have occurred in the past but had not).

Although the pent-up demand does not reflect any sale or service volumes delivered to customers per se, it has to be taken into account during the forecasting process to increase the forecasting accuracy. For example, if a company delivered "X" amount of something, the total demand has to be measured as "X + Y" where "Y" reflects demanded while not delivered to the customers units. Companies notoriously overlook the pent-up demand issue in their operational and strategic activities, which results in distorted forecasting and planning, leading to a general drop in revenue and profit.

Further, any sale volume samples below will indicate a cumulative total amount, containing both historical sales and pent-up demand. A mechanism of the pent-up demand data monitoring, collection, analysis and processing will be considered in one of the further publications.

Time-Series Analysis and Forecasting

"Essentially, all models are wrong, but some are useful"
George E. P. Box; Norman R. Draper

Now, let us briefly review the Time-Series methodological approach.

The main idea of the Time-Series statistical forecasting is to determine common tendencies and seasonality of sales based on the series of observations during a prior period of time, with further extension of the trends and seasonality into the future time period.

Figure 1 shows a sample of the historical sales observations: the unitized sales sample is presented by a four-year long monthly historical data set. A steady growth tendency with a clear-cut annual seasonality is observed.

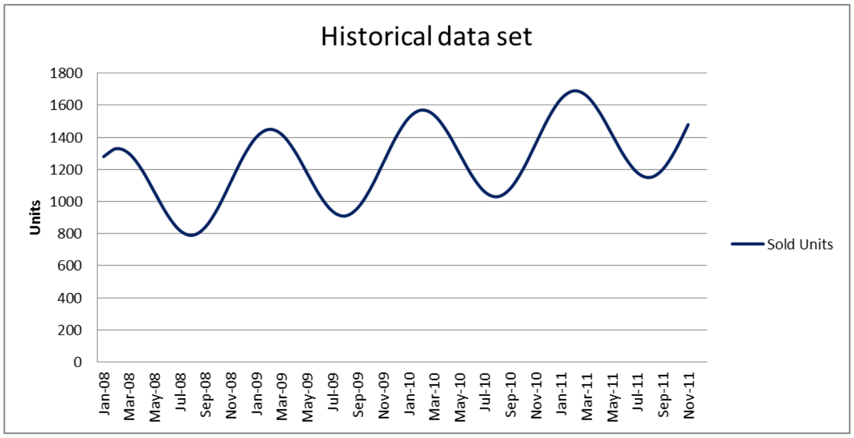

Figure 1. Historical data set – Sample

Technically, the forecasting procedure comprises of three basic stages:

- Historical data (Figure 1) decomposition into a trend and seasonal components (Figure 2: green and red lines, respectively);
- Their further projection into the future (Figure 3: 'Forecast' components); and
- Assembling the forecasted trend and seasonal components into a single forecasting data set (Figure 3: 'Unit Sales: Forecast').

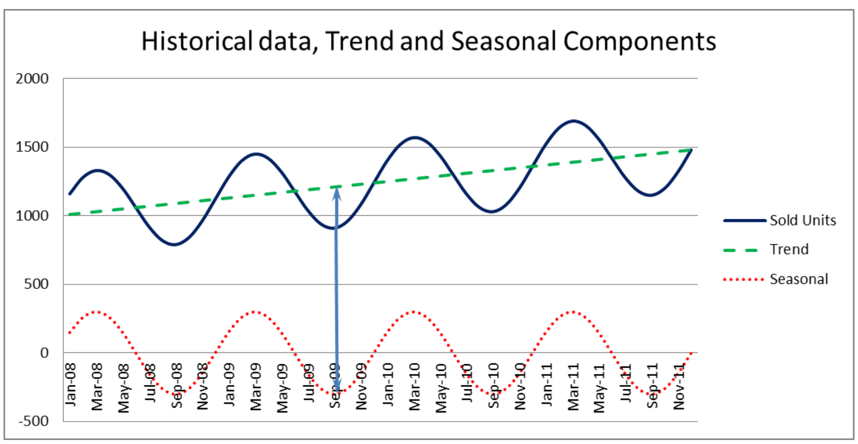

Figure 2. Historical data set – trend and seasonal decomposition

In some particular cases the historical data decomposition may also include long-term cycles and minor short-term fluctuations (so-called "noise") in addition to the trend and seasonal parts. However, in many business cases these elements are neglected due to their rather weak impact.

Further we will consider the most commonly used case described by the trend-and-season forecasting methodology.

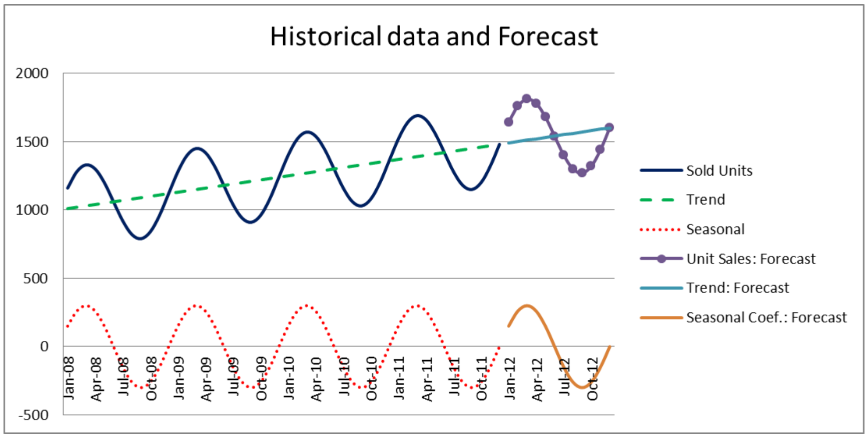

Figure 3. Historical data and Forecast: Model

The above sample case (Figures 1-3) provides an ideal case that rarely occurs in reality. Normally businesses have to face rather more complex scenarios like the one on Figure 4. Here numerous 'peaks' and 'gaps' (marked by circles) spoil the ideal historical sales behaviour shown in Figure 1. The highlighted deviations result from multiple factors like marketing actions and promotions, shortage of goods or capacity, competitors' activity, logistic or manufacturing delays, and many others.

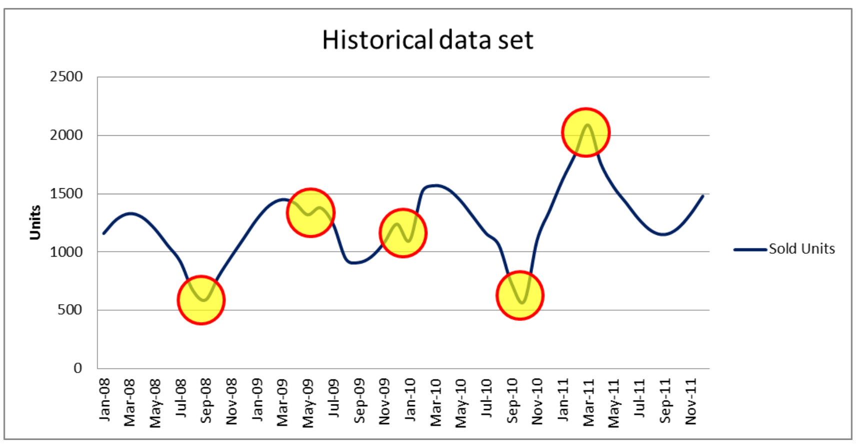

Figure 4. Historical data set with peaks and gaps – Sample

To eliminate the factors from the historical data set ("historical data cleaning") and to align the forecasting model with the "ideal view" (as if nothing unusual happened), a forecaster needs to recognize these impacting factors, and to measure and estimate their influence over the sales volume. Once defined, the impacting factors have to be analyzed, formalized, and collected for the future forecasting issues. Specifically, if any similar occurrences are anticipated in the future (e.g. marketing activities, etc.), a forecaster may apply the formalized factors to the statistical forecasting results (those shown on Figure 3) in order to make the demand anticipation numbers more precise.

As an example, the following five factors (Table 2) are assumed to impact greatly the future sales of the product presented on Figures 1-3. These might be marketing promotions (e.g. factors 1, 2, and 5), manufacturing delays (factor 3), or expiry of a partner agreement (factor 4). The impact factors have to be applied to all the products or groups influenced by these factors.

Impact Factors	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Factor 1		15%										
Factor 2					10%	20%	30%	20%	10%			
Factor 3			-20%								-30%	
Factor 4				-5%	-10%	-5%						
Factor 5									15%	30%	15%	

Table 2. Impact factors

The factors are applied to a 'pure' statistical forecast (Figure 3) in order to transform the "ideal" forecasting view into the "actual" forecast (Figure 5: red line). The latter can further be used for operational and strategic purposes (budgeting, planning, manufacturing, etc.)

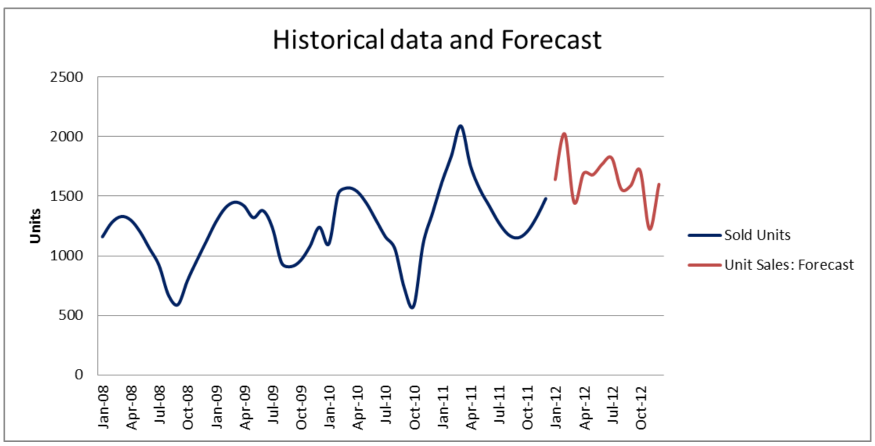

Figure 5. Historical data and Forecast: Actual Model

Therefore, the Time-Series statistical (*quantitative*) forecasting methodology is often extended by expert (*qualitative*) data verification. From the methodological standpoint, the forecasting and planning process includes five main stages (see Figure 6 below):

1. **Data collection**. Includes recognition of demand drivers, and data collection per se – both quantitative and qualitative. The most significant part during the stage is the demand drivers' formalization – in particular, a forecaster has to define the data collection rules (e.g. data sources, data retrieving frequency, pent-up demand data gathering, etc.) and then strictly follow these rules. Also, the collected data has to meet business requirements, and reflect clearly the business goals.

2. **Data verification**. The data verification procedure is a cleaning of the historical data from uncommon events, and transformation of the data into a shape that is suitable for forecasting. Additionally, the considered events are analyzed and formalized for any further application purposes. In particular, any uncommon future event can be

associated with a similar formalized one, to be later applied as an impact factor to a statistical forecast

3. **Statistical forecast**. A methodological approach based on statistical mathematical techniques, producing 'pure' statistical forecasting of the future demand on the basis of the verified historical data set.

4. **Forecasting verification**. This procedure improves the 'pure' statistical forecasting, transforming the "ideal" statistical demand forecasting into the "actual" one (more realistic view) through the implementation of relevant events/factors. In addition to that, the current stage serves for the forecasting model improvement. Specifically, the current demand forecasting data is saved, to be analytically compared with the actual data in the same time horizon. This numerical feedback reveals any possible discrepancies between the model and the actual values, allowing forecasters to recognize the model weaknesses and to address them.

5. **Planning**. Translation of the forecasting results into the business requirements like purchasing or manufacturing volumes, logistic and supply chain events, goods replenishment, budgeting, etc. The stage also provides strategic, operational and other process management-related recommendations to the company.

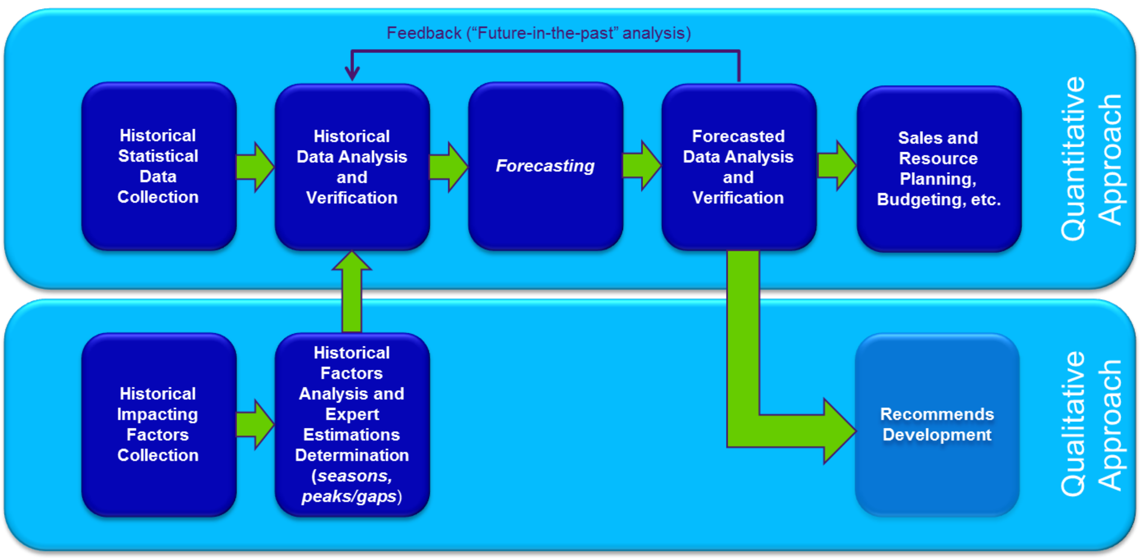

Figure 6. Forecasting Outlines

It is a common fact that many forecasters tend to overlook stages 2 and 4, primarily focusing on stage 3 only. This may result in reduced forecasting accuracy and even in wrong outputs due to overlooking of the factors that substantially influence anticipation of customer demand. When looking at forecasting stages 2-4 as a whole and for the sake of forecasting accuracy, the amount of time devoted to each stage should be around 40%, 30% and 30%, respectively.

A *"future-in-the-past" analysis* – regular analysis of the forecasting results compared to actuals for the past time horizon – is extremely important tool, enabling forecasters to recognize any methodological weaknesses, as well as providing them with an opportunity to continuously improve their applied methods and approaches. Omission of this action transforms forecasting process into an administrative exercise of little substance and with rather unpredictable results.

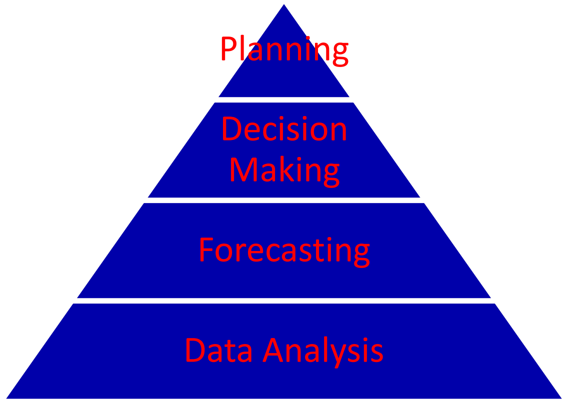

Figure 7. Forecasting Procedures

The whole planning procedure can be described as a pyramid (Figure 7) where the data analysis is the basic and most time-consuming operation. Its elimination (or insufficient accuracy thereof) may result in inaccurate demand forecasting that will affect all the related business operations. Data analysis includes statistical historical data research as well as any related permanent feedback from peers like sales, marketing, manufacturing, etc.

The Time-Series forecasting methodology option is also essential part of the forecasting process. A forecaster must very carefully choose a statistical forecasting method that is right for the given circumstances.

Business Case: Multi-Methodological Forecasting Approach

The Approach Review

"Any customer can have a car painted any color that he wants… so long as it is black"
Henry Ford

Looking back at Henry Ford's business model, it gets become evident that his approach of providing no-choice black color only vehicles worked well initially, but began dragging his business down, as customer expectations and diversity of competitors' offers increased.

Forecasting is the same in the sense that a single, universally applied statistical methodology – *an approach commonly favored by beginners* - may work well initially and for certain single cases, yet is incapable of coping with the huge diversity of existing data sets. For this reason alone a good forecaster should always operate a wide variety of statistical methods with different attributive characteristics.

Below, we will consider a case that clearly reflects the multi-methodological approach benefits.

The business case examines the feasibility of using a multi-method time-series approach to make a demand forecasting model, and to demonstrate the value of such approach for successful business optimization.

Sample Conditions and Problem Goals

There are three sample items – A, B and C – whose historical unit sales are represented by discrete monthly data sets, spanning four years (48 observations per item in total); each of the items possesses strong seasonality. To simplify the considered sample case the data verification is neglected, assuming conditions are already verified for the presented historical data sets.

The main goal of the exercise is to make an annual sales forecast for each item, broken down into monthly view, with further purchasing planning and budgeting for the same time horizon. Additionally, we will briefly cover unitized pricing and segmentation approaches.

Statistical forecast: Problem Overview

The considered sample is represented by three items – A, B, C – which historical monthly consumption is shown below (see Figure 8, Table 3).

All of the items possess strong growing trend and seasonality, having clear annual seasonal peaks in July. However, each item possesses a specific behaviour from the point of the historical time horizon. Namely,

- Product A demonstrates very constant annual sales behaviour. That can be expressed by a linear trend and identical monthly-based seasonal coefficients.

- Product B demonstrates steady growth with the seasonality proportionally increased year-to-year.

- Product C shows steady growth – both trend and seasonality – in the first three years, then surges dramatically in the fourth year.

Thus, having demonstrated quite a similar annual behaviour in general, each of all three products still possesses very different attribute characteristics of its own. Therefore, application of a single forecasting methodology to all of them might be wrong, and the most appropriate methodology has to be determined to each data set. For this particular case, we will consider statistical forecasting methodologies that possess additive, multiplicative, and varying features.

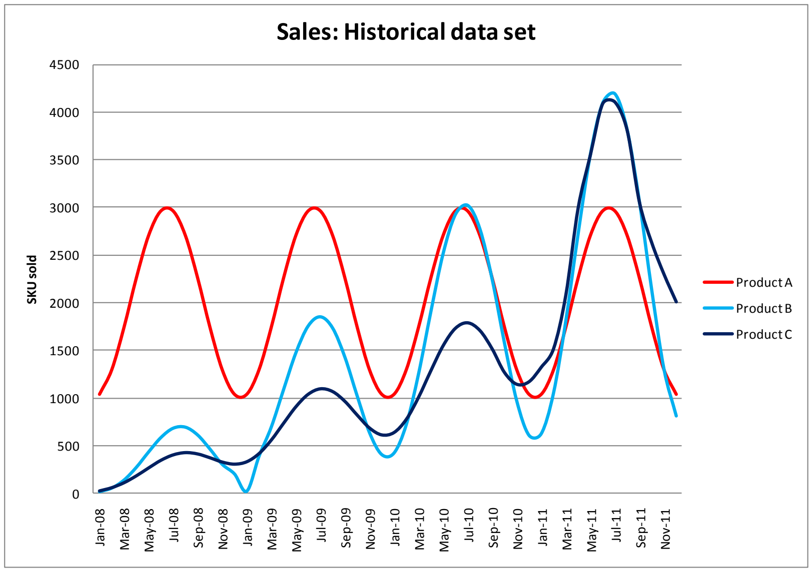

Figure 8. Historical sales of Products A, B and C (graphs)

	Product A				Product B				Product C			
	2008	2009	2010	2011	2008	2009	2010	2011	2008	2009	2010	2011
Jan	1,034	1,134	1,234	1,334	17	22	422	625	26	332	639	1,325
Feb	1,293	1,393	1,493	1,593	55	388	720	1,052	60	418	777	1,518
Mar	1,741	1,841	1,941	2,041	139	695	1,252	1,808	112	560	1,009	2,081
Apr	2,259	2,359	2,459	2,559	272	1,087	1,902	2,717	184	736	1,287	2,992
May	2,707	2,807	2,907	3,007	433	1,472	2,512	3,551	267	909	1,550	3,551
Jun	2,966	3,066	3,166	3,266	584	1,753	2,922	4,090	347	1,040	1,733	4,090
Jul	2,966	3,066	3,166	3,266	682	1,850	3,019	4,188	404	1,098	1,791	4,109
Aug	2,707	2,807	2,907	3,007	693	1,732	2,771	3,811	428	1,069	1,710	3,811
Sep	2,259	2,359	2,459	2,559	611	1,426	2,242	3,057	414	966	1,517	3,057
Oct	1,741	1,841	1,941	2,041	464	1,020	1,576	2,133	374	822	1,270	2,633
Nov	1,293	1,393	1,493	1,593	304	637	969	1,301	329	687	1,146	2,301
Dec	1,034	1,134	1,234	1,334	203	406	608	811	307	614	1,172	2,011

Table 3. Historical sales of Products A, B and C (tables)

Statistical forecast: Multi-Method Approach

Product A

As Product A shows quite stable annual behaviour with repetitive seasonal coefficients (see Figure 8; Table 3), a forecasting methodology with additive attributes looks like the most appropriate here. Such methodologies are usually applied to statistical data sets with a well visible trend (linear or non-linear) and uniformly increasing/decreasing seasonal coefficients (“adding” a value to the past year(-s) seasonal data).

Fairly stable conditions of the historical data set often produce linear trend. Trends described by other functions (e.g. Exponential, Logarithm) will show similar – close to linear – views for a one-year forecasting horizon. As seasonality for Product A is repetitive and strongly marked, with close Y-2-Y monthly volumes, the following year behaviour seems to be pretty similar.

The applied additive-based statistical method provides quite accurate result (Figure 9; Table 4) with the confidence level (RMSD[1]) less than 1%. Although a better accuracy could be achieved through application of additional forecasting methods, this is considered as overkill, since the approach already implemented provides reliable results while the accuracy level sufficient to meet requirements of the majority of businesses.

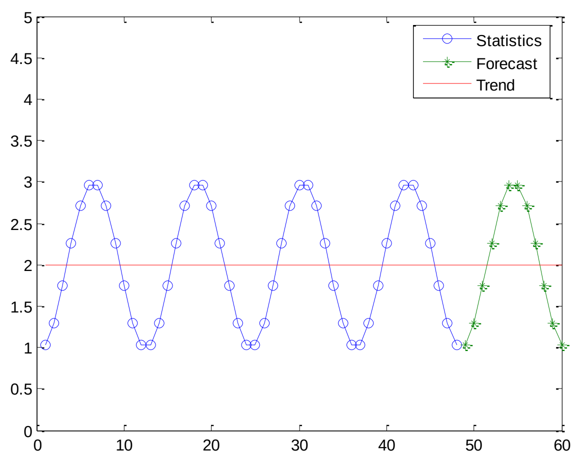

Figure 9. Product A:
Historical data, Trend and Forecast (additive method)
SKU*10^3; 60 months data set

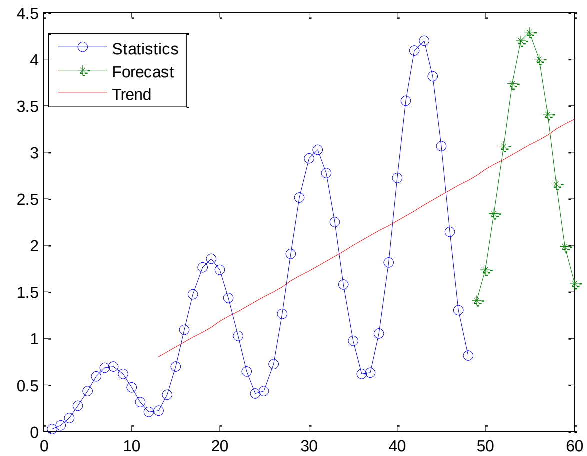

Figure 10. Product B:
Historical data, Trend and Forecast (additive method)
SKU*10^3; 60 months data set

Product B

Historical data of Product B, as shown in Figure 8 and Table 3, reflects year to year steady growth of the product sales. Similar to Product A, the trend here is close to linear, and seasonal adjustments happen in the same months. However, seasonal fluctuations continuously increase from year to year and that, combined with the growing trend, leads to its tendency for multiplicative behaviour.

Similarly to the first sample, the additive-based methodology is applied to the set of the existing historical data (see Figure 10). However, the forecasted data span hardly reflects the general sales behaviour. Assuming that no additional factors could influence this historical data set, the forecasted result was expected to show Y-2-Y growth for the same months. Despite a fairly small deviation (2.8%), the applied methodology looks inappropriate for Product B.

As the statistical time-series behaves multiplicatively (*seasonal coefficients growth occurs proportionally from year to year with respect to the trend*) a forecasting approach with a multiplicative attribute seems quite suitable in this particular case.

[1] RMSD – Root-mean-square deviation between the observed and modeled values: determines borders of a confidential interval.

Compared to Additive-based, Multiplicative-based methodology (MBM) is distinguished by a rather high sensitivity. MBM reflects the statistical data and its behaviour much better (see Figure 11; Table 4). In particular, having determined the linear trend as the most appropriate for Product B data set, the methodology multiplicatively stretched the resulting forecasted data in more prominent numbers for both in-season and out-of-season periods of time. Statistical deviation (0.13%) also confirms the last method as more appropriate for Product B.

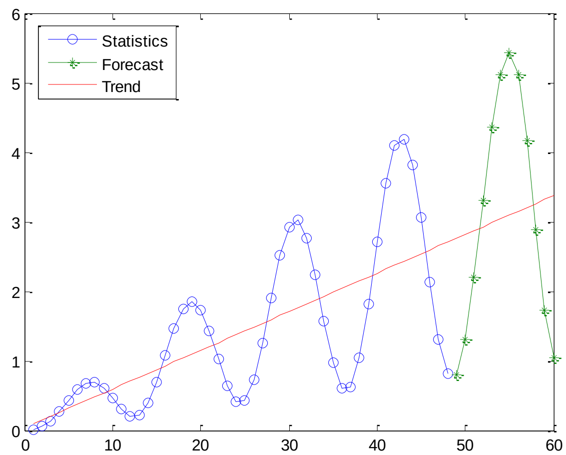

Figure 11. Product B:
Historical data, Trend and Forecast (multiplicative method)
SKU*10^3; 60 months data set

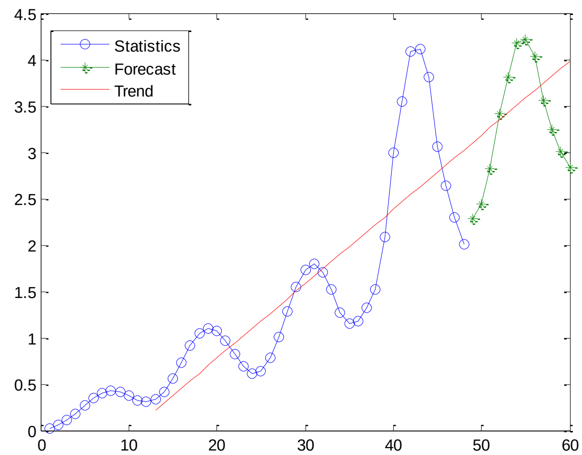

Figure 12. Product C:
Historical data, Trend and Forecast (additive method)
SKU*10^3; 60 months data set

It also has to be mentioned that only two criteria were taken into account in the estimation and selection of the forecasting methodologies for the considered business case – RMSD and annual growth coefficient. The latter reflects Y-2-Y sales volume growth. If it is rather high (e.g. >1.3 without any reasonable cause thereof) or small (<0.5) the forecasting method should not be applied. In the author's mind these criteria are enough to show a simple selection in a case like the considered one. For more complicated business situations more criteria can be used.

Product C

The last considered item shows quite steady sales growth for the first three years while the fourth year is represented by a surge in sales. More specifically, noticeable increase is observed from Q2'11 till the year end. This can supposedly occur due to some market or internal events. As before, we will disregard the events (assuming that this activity has been accomplished) and only analyze the statistical data.

In case of such statistical data set any linear (or close to linear) trends applied to the whole historical time horizon would be rather questionable because of the statistical time-series non-linearity. Under these circumstances, three forecasting methods with different attribute characteristics – additive, multiplicative and mixed – are applied to demonstrate why the multi-methodological approach should be utilized.

The first – additive-based – forecasting method shows growing linear sales trend, while the forecasting results for 2012 do not reflect any growth (see Figure 12). Even more, the top-season sales are approximately the same as they were the year before. The deviation is rather high (around 6.3%) in comparison with other methods (as will be further shown), making the additive-based approach unsuitable for this particular Product C.

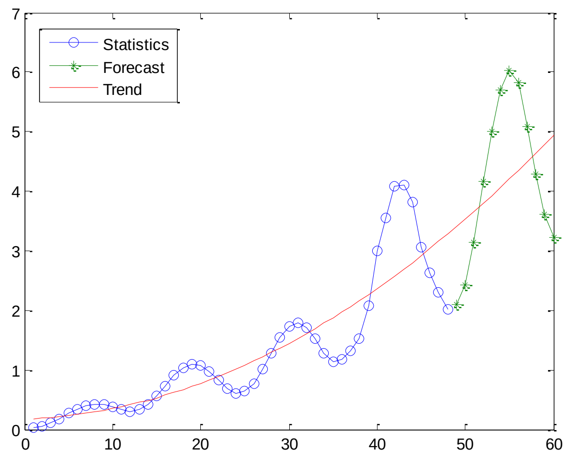

Figure 13. Product C:
Historical data, Trend and Forecast (multiplicative method)
SKU*10^3; 60 months data set

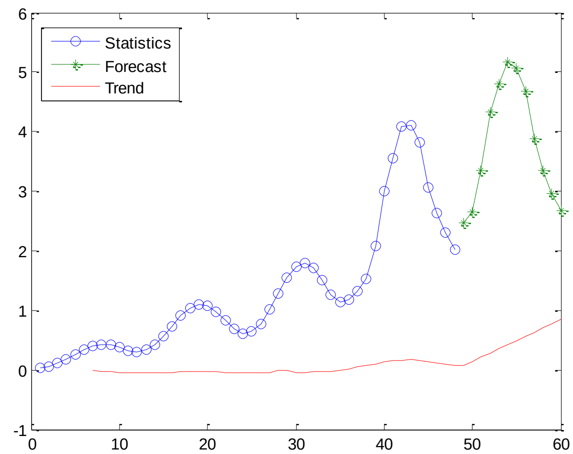

Figure 14. Product C:
Historical data, Trend and Forecast (variative method)
SKU*10^3; 60 months data set

The second – multiplicative-based – approach results in quite different way, namely predicting too aggressive sales expansion based on dramatically growing seasonal coefficients intensified by exponentially increasing trend (see Figure 13). Possessing the most optimistic sales forecast among others with the least RMSD (1.1%), the method is considered unsuitable as well, this time due to high annual growth coefficient.

The last considered approach is based on Holt-Winters technique, which possesses the moving average trend-line and is more sensitive to local changes. It appears to be the most appropriate for Product C demand forecasting because of having rather small deviation (4.2%) while providing adequate accuracy for expected sales values for 2012 (see Figure 14). It forms the most accurate annual sales and purchasing plans, as well as budgeting.

A comparative review of all three results for Product C (Figure 15) shows that the one based on the Holt-Winters methodology looks like the most affordable and the least risky.

Analysis of all three Products – A, B and C – and rounding up the best demand forecast methodological approach for each product result in the following 2012 sales forecast (see Table 4).

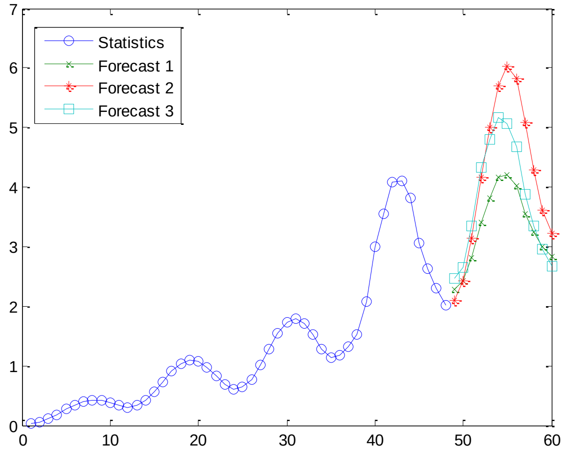

Figure 15. Product C: Historical data and Forecasts (additive: Forecast 1, multiplicative: Forecast 2 and Holt-Winters based: Forecast 3); SKU*10^3; 60 months data set

	Product A 2012	Product B 2012	Product C 2012
Jan	1,034	803	2,463
Feb	1,293	1,308	2,657
Mar	1,741	2,207	3,349
Apr	2,259	3,304	4,323
May	2,707	4,359	4,800
Jun	2,966	5,113	5,175
Jul	2,966	5,435	5,073
Aug	2,707	5,109	4,680
Sep	2,259	4,159	3,878
Oct	1,741	2,888	3,349
Nov	1,293	1,728	2,953
Dec	1,034	1,051	2,678

Table 4. 2012 Product Forecast (units).

Based on the provided results, sales and procurement teams will be able to create monthly and annually unitized (and further monetized) plans with very high level of accuracy. The latter is a great benefit for any company due to its flexibility, as well as ability to cost saving.

Budgeting

To complete the case, the above unitized forecast (Table 4) has to be transformed into a budget through monetary expression of purchasing and sales operations.

Since market stability is assumed for the considered business case, purchasing and sales prices, while delivery time[2] is fixed in the model. In particular, sale prices of the items are assumed at $50.00, $100.00 and $150.00 for A, B and C units respectively. Purchasing prices for each position are assumed at $30.00, $90.00 and $130.00, while delivery time is assumed at 1 month for Product A, 2 months for Product B, and 3 months for Product C.

Multiplication of the forecasted demand data (Table 4) with the above pointed sale and purchasing prices results in annual cash flow consisting of incoming and outgoing portions that finally result in contribution margin (see Figure 16). The purchasing portion is moving left for a few months to align the data through the delivery time. For the sake of simplicity the model also omits any account payable and accounts receivable shifts, discounts, etc. In real life the model is substantially more sophisticated.

Using the above data, a financial team is able to 'play' with implementation of additional financial modules like credit lines, investments, and other elements, in order to move the

[2] In the real business models such factors as varying of the prices, delivery terms and conditions, etc. have to be taken into account as variable components with a regular (e.g. monthly) data analysis and verification

"Delta" value to the desirable position. Undoubtedly, the final plans and budget are not set in stone, and may and will vary during the year (monthly and quarterly). Nevertheless, these fluctuations will not impact a lot, and the general view will be quite stable.

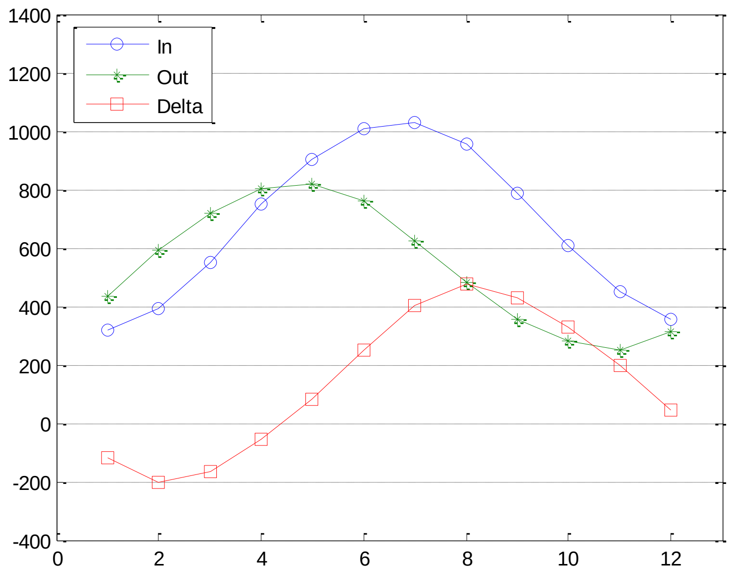

Figure 16. Cash flow – Forecast ($$)
("In" – Sales, "Out" – Purchasing, "Delta" – Contribution Margin)

Pricing

To improve accuracy of the financial forecasting, unitizing prices should be determined in the manner similar to the one applied to the unit demand forecasting. The unit price level during the determined planning horizon should be calculated discretely (e.g. monthly, or otherwise, depending on the current market conditions). To achieve it, two basic methods are commonly applied:

- Historical statistical pricing analysis and future term forecasting akin to the unitized forecasting approach.

- Marketing estimation of the pricing level.

The latter is required to align a company's pricing strategy with market conditions. Here, a unit price depends on three main parameters: net cost of a unit in stock (depends on prices of all the similar units); contribution margin determined by e.g. Finance Department as the bottom line in terms of general company's profitability; and weighting average market price based on main competitors' price-tag and their market shares. The latter is expressed as follwing

Competitor Name	Price-tag (PT)	Weight Function (WF)
AAA	X	50%
BBB	Y	35%
CCC	Z	15%

where the unit price is counted as SUM(PT_i * WF_i).

The following sample (Figure 17) displays the approach in a graphic view. Here

- "Red zone" depicts the net cost level that sets the bottom line of a unit price – the latter cannot move into this zone except for special conditions (e.g. clearance sale);
- "Amber zone" means the level determined as a company's profitability – a pricing specialist should keep the unit price upper this level, however some variations within the "Amber zone" are acceptable (e.g. discounts for some customers);
- "Green zone" delimits the most appropriate pricing level – a pricing specialist is advised to operate the unit price within this area; and
- "Orange zone" is a level that push the unit price upper than major competitors' ones – it is not recommended to move the pricing level into this particular zone except for special market conditions.

This approach allows a company to vary its pricing level between the bottom-line (general profitability or net-cost) and rivals' pricing level that results in providing better market pricing conditions and higher flexibility.

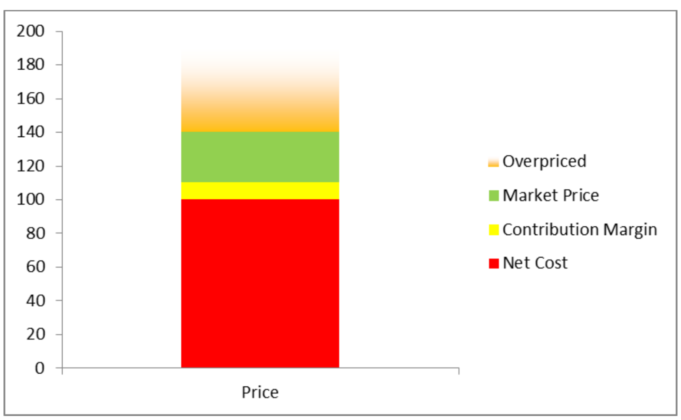

Figure 17. Pricing – Sample ($$)

Therefore, using the historical actual, as well as estimated price fluctuations as a benchmark, a forecaster will be able to determine the pricing level per unit, and then apply the data to the financial forecasting model.

Goods and services segmentation

Running a large and diverse inventory is common for many businesses, making it almost impossible to produce an accurate forecast for each inventory item. Moreover, it is usually a relatively small percentage of such inventories that are actively demanded. To simplify the forecasting and planning procedures and to improve the operational efficiency the Pareto's Law should be implemented into the business operations.

According to the Pareto's Law, the products' top 20% bring 80% of revenue, while the other 80% of products produce the remaining 20% of revenue. Many companies follow this ratio to the letter or with only minor alterations. The so-called "ABC Methodology" is often applied, by breaking the product revenue down into "the top 80% product revenue segment" (group A), "average 15%" (group B), and "bottom 5%" (group C). It should be mentioned, the approach is often applied regardless of the product demand frequency, any manufacturing and/or distribution terms, etc. It is fairly common case when a product is in "Group A" because of its highly monetized sales volume only, even if it is sold infrequently (e.g., twice a year). That forces a forecaster to focus excessively on such product, while neglecting other items with less per-item revenue but with higher demand. These latter products might generate much higher compound monetized effect – if said forecaster attended to them a bit more, and applied more sophisticated approaches into the product segmentation.

Each company is quite unique, so to increase its general efficiency and profitability, an individual approach should be applied to each particular case. New parameters, like demand frequency or unitized sales volume should be added to the segmentation criteria. The range of parameters is broad, and each company has to define them in terms of its development strategy, and to modify the Pareto's Law depending on those definitions.

Below is an example of a simple product segmentation case – a modified Pareto's Law that depends on both revenue and product demand frequency. In this particular case, product items are separated into Groups A, B and C by their monetized value (as shown above), while the product demand frequency is reflected via X, Y and Z groups.

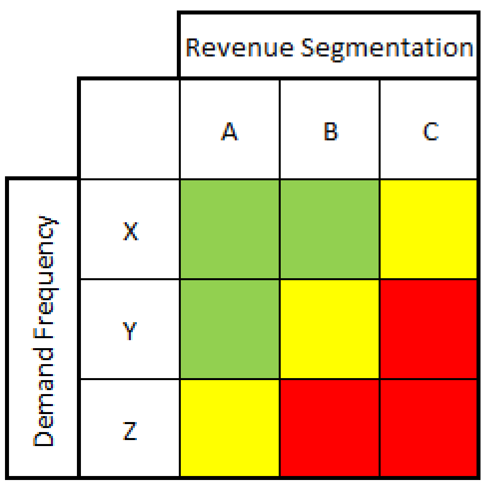

Table 5. Product Segmentation

The items that are more frequently demanded (top 70%) form Group X, items with quite rare demand form Group Y (average 20%), and items with a few annual demand (bottom 10%) end up in Group C. As a result, ABC-XYZ matrix (see Table 5) forms new product segmentation, where the green squares reflect the top-priority (daily checking) products, the yellow ones are for the mid-priority (weekly to monthly checking) items, and the red squares reflect the bottom priority (monthly to quarterly checking) items. A forecaster should first focus on the green squares, by applying detailed data verification and analysis, as well as precise and highly sophisticated forecasting methodologies to this group. The yellow squares will require less attention and simpler forecasting methods. And only averaged or intuitive approaches will be applied to the red squares.

Such segmentation and priority determination of the forecasting groups allows businesses to meet their vital needs, but with much better forecasting and resource planning efficiency. The latter results in big cost saving.

Conclusion

"Now, here, you see, it takes all the running you can do, to keep in the same place. If you want to get somewhere else, you must run at least twice as fast as that!"
Alice's Adventures in Wonderland, Lewis Carroll

This white paper primarily addresses both theoretical and practical aspects of forecasting and resource planning approaches, i.e. how to do it in the most accurate way and ultimately to improve general procurement efficiency. In particular, we outlined some common causes for deterioration in assets and business performance that ensued from incorrect material management approaches. We also considered some appropriate methodologies and business cases that can be used to correct the modeling and then to improve business efficiency and profitability.

It has to be mentioned that indirect savings are quite difficult to quantify in precise dollars. However, many companies, that proactively implemented advanced and innovative technologies into their business processes, moved ahead dramatically.

Read the Red Queen's quote in the beginning of the paragraph. Its purpose is to prompt readers – especially newbie demand forecasters and resource planners – to act deliberately and proactively through applying powerful and flexible science-based approaches in their work. Eventually, forecasting and resource planning are much more that a set of technical skills or magic formulae, so for any sales or service enterprise focusing on them is a big strategic step in the right direction.

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