Volume 4, Number 1, 2007, pp. 61-87

Multiproduct supply chain - Strategic planning and forecasting

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Abstract

The relation among the actor's of the Supply Chain defines its main characteristics, and therefore the Distribution and Manufacturing Strategy that the actors must follow in order to fulfill the Service Equation. In a Multiproduct Supply Chain, the different *Negotiating Force* of the different actors will truly influence in the final design on the Chain Configuration. Depending on which actor has more power, the Supply Chain must react to different supply policies. Forecasting Tools are presented as an option to predict the *product Distribution and Manufacturing needs* and as a way to counterbalance the different negotiating force among actors.

Key words: Logistics, Business Strategy, Forecast, Distribution & Multiproduct Manufacturing.

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INTRODUCTION

Today's world is becoming a global market with disappearing boundaries. Nowadays, one of the critical constraints for companies, are the accuracy of manufacturing, movement, and storage for the products along the Supply Chain, within the functions that make it possible to happen: according to Chopra *et al.* (2004) "distribution refers to the steps taken to move and store a product from the supplier stage to a customer stage in the Supply Chain". In order to have products moved and commercialized, the manufacturing function is needed along the Supply Chain since it works as the chain's *supplier*. According to Bowersox *et al*. (2002) "manufacturers add value by converting raw materials into consumer or industrial products", since manufacturing takes time in terms of production processes, *production lead times* tends to be longer than *distribution lead times* and so manufacturing processes are more forecast-dependent than distribution processes; in a MTP/MTS context (Make-to-Plan/ Make-to-Stock); see Bowersox *et al*. (2002)). Transportation, Distribution, Storage and Manufacturing Logistics play a critical role in the Service Equation: Delivery Time, Place, Quantity and Cost.

The relationship between the actors of the Supply Chain defines the Distribution and Manufacturing Strategy that the actors must follow. It is required then, to analyze the business characteristics and to determine which is the most convenient strategy to fulfill the Service Equation, and later on, materialize this strategy in the Company's logistic procedures in order to make it happen.

This paper is organized as follows: section 2 gives an overview of what we propose as a Basic Supply and Distribution Network model; in section 2.1 we propose an application of the Quantitative Forecasting Tools within this Basic Distribution Network; later on we propose the Multi-product Distribution Network model; in section 2.2 we propose an application for Qualitative and Quantitative Forecasting Methods in terms of the *"Method Category-Aggregation Level* Matrix*"* applied to a Manufacturing context; this matrix proposes an application of forecasting techniques for a Multiproduct Manufacturing environment, which consists in an integration of the Quantitative and Qualitative Forecasting methods and the different potential aggregation degrees of the products. In section 3 we propose a categorization of the different Negotiating Force scenarios between Customer and Supplier that must be taken into account in order to plan the Distribution and Manufacturing Strategy, to strategically deal with important customers. Section 4 proposes some final conclusions.

STRATEGIC PLANNING FOR THE SUPPLY CHAIN NETWORK

Knowing the market and the environment where the business develops is an important step to define the Supply, Production, and Distribution Policies. There are many different kinds of Distribution Network configurations that have evolved during the years, depending on the nature of its Business and the power of its actors: suppliers, customers and market. In order to study these networks we propose to reduce this diversity and to study the simplest network. Once it has been studied, it will be possible to make conclusions and, later on, generalize them to the complexity of the entire Network. Let's propose the following Basic Supply and Distribution Network:

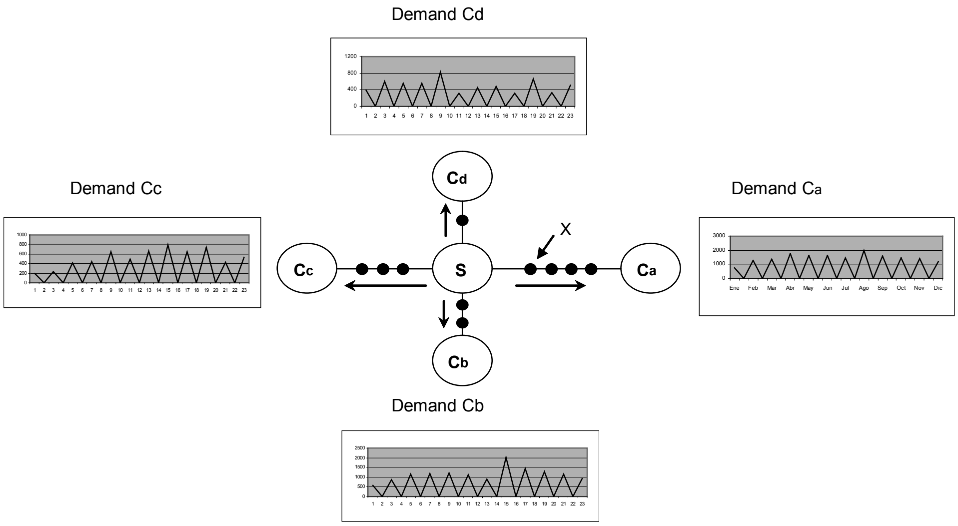

Figure 1. Basic Supply and Distribution Network and Demand Profile for each C_i

i. Let C_i be the Customer who demands product from S. C_i may have other demands confirmed by other(s) Customer(s) not showed in the drawing.
ii. Let S be the Supplier for C_i (for i=a,b,c and d; the Basic Network could have *n* Customers).
iii. Let X be one Product that moves along the network according to C_i's demand.
iv. Each C_i is supplied of Product X exclusively by the Supplier S.
v. For each C_i, we have the recent historical Monthly Demand (sales curve). Demand behavior is similar for every C_i.
vi. Supplier S supplies uniquely its Product X to the Customers C_i's. S has to work out the Production and Distribution Plan for Product X according to its customers needs.
vii. Suppose that transportation time is relatively short, so it is possible to approximate the Global Demand for S (in terms of time and quantity), as the sum of the individual demands in each C_i.
viii. Suppose that transportation cost is high, so transportation cost is very sensitive to freight consolidation.

Now, which strategy must the Supplier S follow in order to create a Supply Policy for its Customers C_i? Are all its C_i Customers asking for more product than needed? Can S trust this current sales data in order to make a global prediction? Is Supplier S pushing the product to its C_i's so there will be big chances that global demand decreases because of overstocking at each C_i's warehouse? How can the Manufacturer produce in order to supply according to the Distribution needs?

DISTRIBUTION FORECASTING

Within the cooperation frame between enterprises categorized as S and C, it is very important to foster the mutual collaboration when building the Operations Plans: Demand Plan, Production Plan and the Distribution Plan. Relationships between non-collaborating enterprises show supply problems such as: product stockouts, overstocking, considerable forecasting errors, etc.

Many of these problems come from some companies' lack of cooperation and the differences in Negotiating Forces that exists among the actors in the network; differences that we will comment at the end of this publication. Based on a policy of mutual collaboration between S and C, how can a forecast be calculated in order to have a distribution plan (time and quantity) through a Basic Supply and Distribution Network? We propose to do this using Quantitative Forecasting Tools. Historical Demand data for Product X and four C's (four Customers) is showed in Figure #2.

Sales History												
Sales; Liters	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Year 2003												
Item	Real	Real	Real	Real	Real	Real	Real	Real	Real	Real	Real	Real
Customer A	766	1,279.68	1,363	1,784.70	1,646	1,641.74	1,460	2,005.26	1,610	1,437.45	1,399	1,204.60
Customer B	575	863.04	1,153	1,189.80	1,213	1,106.39	904	2,005.26	1,449	1,273.17	1,166	919.30
Customer C	192	238.08	419	436.26	650	499.66	661	791.55	644	739.26	433	538.90
Customer D	383	595.20	559	555.24	823	321.21	452	474.93	322	657.12	333	507.20
total	**1,916**	**2,976**	**3,495**	**3,966**	**4,332**	**3,569**	**3,477**	**5,277**	**4,024**	**4,107**	**3,332**	**3,170**
Year 2004												
	Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
	Real	Real	Real	Real	Real	Real	Real	Real	Real	Real	Real	Real
Customer A	1,444	1,534	2,253	2,351	1,755	2,439	2,087	2,050	2,675	1,685	2,370	1,807
Customer B	1,083	1,035	1,907	1,568	1,293	1,644	1,292	2,050	2,408	1,492	1,975	1,379
Customer C	361	285	693	575	693	742	944	809	1,070	867	733	809
Customer D	722	714	924	732	877	477	646	486	535	770	564	761
total	**3,611**	**3,568**	**5,778**	**5,225**	**4,618**	**5,303**	**4,968**	**5,395**	**6,688**	**4,814**	**5,642**	**4,756**
Year 2005												
	Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
	Real	Real	Real	Real	Real	Real	Real					
Customer A	1,470	2,536	3,208	3,166	3,062	3,057	2,898					
Customer B	1,103	1,710	2,714	2,111	2,256	2,060	1,794					
Customer C	368	472	987	774	1,209	930	1,311					
Customer D	735	1,180	1,316	985	1,531	598	897					
total	**3,676**	**5,898**	**8,225**	**7,035**	**8,058**	**6,646**	**6,900**					

Figure 2. Basic Supply and Distribution Network. C_i Sales/Demand History for S

In order to forecast demand, we can use several well-known Quantitative Forecasting Methods: Moving Average, Simple Exponential Smoothing, Trend Corrected Exponential Smoothing (Holt's Model), Trend and Seasonality Corrected Exponential Smoothing (Winter's Model) and the Static Method, among the most popular forecasting methods according to Chopra *et al*. (2004). It is not an objective of this article to explain the algorithm of each forecasting method, but to set a guideline of an application of these methods in a Distribution context.

Following the Model showed in Figure #1, and calculating the Forecast for the Global Demand according to data showed in Figure #2, we can see the results in the following comparative chart. For each of the Forecasting Methods we have compared the most common Forecast Evaluating Measures (Error, Absolute Error, MAD (Mean Absolute Deviation), and MAPE (Mean Absolute Percentage Error)). Based on this, is possible to evaluate the convenience of choosing one method (see Figure #3).

Summary Table **Forecasting Effectiveness Indicators**				
Method	MAD Mean Absolute Deviation	MAPE Absolute Percentage	TSt Tracking Signal	
Moving Average	896	17	-11,29	-0,22
Simple Exponential Smoothing	1063	24	-9,37	11,07
Trend Corrected Exponential Smoothing (Holt's Model)	760	17	-3,78	5,19
Trend and Seasonality Corrected Exponential Smoothing (Winter's Model)	411	9	-3,62	5,90
Static Method	372	8	-3,91	5,27

Figure 3. Forecast Evaluating Measures for the Global Demand Forecast.

The best MAPE (8% in this case) is related to the Static Method. The second best MAPE is related to the Winter's Method which shows 9%. When analyzing the MAD, the best values are related to the Static and the Winter Method with 372 and 411 units. Simple Exponential Smoothing method yields a variation (1063 units) that exceeds the double of the variation related to the Winter's Model. MAD is related to the random component of the demand, so, the bigger the MAD, the forecast for the real demand becomes more variable. According to Chopra *et al*. (2004) "the MAD can be used to estimate the standard deviation of the random component assuming that the random component is normally distributed".

The Holt's, the Winter's and the Static methods show the steadiest Tracking Signal values. Tracking Signals measure the consistency of the method according to its capacity to not to bias its predictions. One biased prediction can consistently over or underestimate demand; the normal bias will fluctuate around zero since it will be random; please refer to Chopra *et al*. (2004).

In this case, either the Static Method or the Winter's Method would be chosen over the others methods. The convenience of using the Winter's Method rather than the Static Model is that Winter's has a dynamic characteristic, since this method takes into account the evolution of new demand and changes the Method's parameters (Level, Tendency and Seasonality Factors). On the other hand, the Static Method does not change; the parameters of the initial calculations are used until the initial calculation is run once again. Winter's Method (because of its self-changing properties) is convenient for multiproducts environments (since many different products can be forecasted without having to recalculate the parameters each time).

It is also possible to calculate an individual forecast for each network's node; the same Winter's analysis could be done for each C_i node. It is up to the analyst to set the convenience of the aggregation level for the forecasting, since for many cases it would be important to calculate the forecast for all the nodes as a big node, and in other cases it would be important to calculate each node's forecast (for example, if it is the case of a Distribution Center that supplies all nodes, it is useful to calculate the forecast for the four nodes as a big node since we want to forecast the demand that will be allocated to this Distribution Center; later on we will distribute product to each node). Decision must be based on the real network's features and the possibility to postpone Distribution based on pull requirements and transportation feasibility.

Please refer to the next figure #4 Winter's Method Evaluation for C_a node showing the Winter's calculations for this node. Same calculations should be done when forecasting C_b, C_c and C_d demands.

Trend and Seasonality Corrected Exponential Smoothing (Winter`s Model)

Alfa= 0.05 Beta= 0.1 Gama= 0.1

year	month	period	demand Dt	Level Lt	Trend Tt	Seasonal Factor, St	Forecast, Ft	Error, Et	Absolute error, At	Mean Squared Error, MSEt	MADt	%Error	MAPEt	Tracking Signal TSt
		0		1090	52									
2003	1	1	766.4	1140	52	0.70	800	34	34	1125	34	4	4.38	1.00
2003	2	2	1279.68	1198	53	0.98	1172	-108	108	6386	71	8	6.41	-1.05
2003	3	3	1363.05	1245	52	1.19	1491	128	128	9713	90	9	7.40	0.60
2003	4	4	1784.7	1302	53	1.28	1657	-127	127	11341	99	7	7.33	-0.74
2003	5	5	1646.16	1362	53	1.09	1481	-165	165	14545	112	10	7.88	-2.13
2003	6	6	1641.74	1415	53	1.17	1661	19	19	12182	97	1	6.76	-2.27
2003	7	7	1460.34	1466	53	1.02	1504	43	43	10710	89	3	6.22	-1.98
2003	8	8	2005.26	1530	54	1.14	1738	-267	267	18281	111	13	7.10	-3.98
2003	9	9	1609.6	1577	53	1.13	1786	176	176	19696	119	11	7.53	-2.26
2003	10	10	1437.45	1636	54	0.82	1339	-98	98	18689	117	7	7.46	-3.14
2003	11	11	1399.44	1680	53	0.94	1584	184	184	20072	123	13	7.98	-1.48
2003	12	12	1204.6	1728	53	0.74	1276	71	71	18821	118	6	7.81	-0.93
2004	1	13	1444.4	1795	54	0.70	1242	-203	203	20530	125	14	8.28	-2.51
2004	2	14	1534.24	1834	52	0.99	1833	299	299	25458	137	20	9.08	-0.10
2004	3	15	2253.42	1888	53	1.18	2232	-22	22	23792	130	1	8.54	-0.28
2004	4	16	2351.25	1935	52	1.29	2497	146	146	23639	131	6	8.40	0.84
2004	5	17	1754.84	1967	50	1.10	2195	440	440	33624	149	25	9.38	3.69
2004	6	18	2439.38	2020	50	1.17	2364	-76	76	32073	145	3	9.03	3.28
2004	7	19	2086.56	2069	50	1.02	2115	28	28	30428	139	1	8.63	3.63
2004	8	20	2050.1	2101	48	1.16	2461	410	410	37329	152	20	9.20	6.00
2004	9	21	2675.2	2162	50	1.12	2400	-275	275	39161	158	10	9.25	4.04
2004	10	22	1684.9	2203	49	0.83	1830	145	145	38335	158	9	9.22	4.97
2004	11	23	2369.64	2267	50	0.93	2086	-283	283	40156	163	12	9.34	3.07
2004	12	24	1807.28	2325	51	0.73	1697	-111	111	38993	161	6	9.20	2.42
2005	1	25	1470.4	2361	50	0.71	1682	212	212	39228	163	14	9.41	3.69
2005	2	26	2536.14	2420	50	0.98	2352	-184	184	39018	164	7	9.33	2.55
2005	3	27	3207.75	2482	52	1.18	2925	-283	283	40544	168	9	9.31	0.80
2005	4	28	3165.75	2531	51	1.28	3243	78	78	39311	165	2	9.06	1.28
2005	5	29	3062.04	2595	53	1.08	2798	-264	264	40359	168	9	9.05	-0.31
2005	6	30	3057.16	2645	52	1.18	3112	55	55	39116	164	2	8.81	0.02
2005	7	31	2898	2704	53	1.02	2752	-146	146	38540	164	5	8.69	-0.87

Forecast Equation Ft+l = (Lt + lTt) * S t+l

1	8	32				1.14	3151
2	9	33				1.13	3172
3	10	34				0.82	2351
4	11	35				0.94	2737
5	12	36				0.74	2188

	Coeficients
Interception	1090.32
Variable X 1	52.266

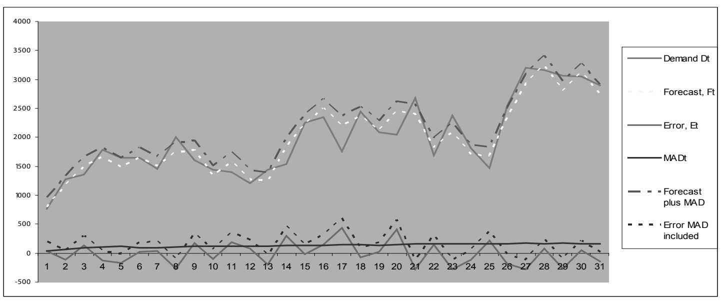

Figure 4. Winter's Method Evaluation for C_a node

Some remarks related to figure #4 are:

- We propose the use of the graphic tool as a way to display and, therefore, understand the effectiveness of the forecasting method along recent historic data.
- Negative Forecast Error represents stockouts (when the forecasted line is below the demand line this represent a stockout); positive Forecast Error is related to overstocking.
- Using MAD, it is possible to estimate the standard deviation of the demand's random component. Using this criterion, it is possible to set a policy of *Safety Inventory*, due to the fact that if we add a MAD factor to the Forecast, it is possible to reduce the possible stockouts using higher inventory level at each node; also a global Safety Inventory can be set in S and "*Pull*" according to each node's requirements.
- The *Forecast plus MAD* line (semi-continuous green line) is exactly the same line that the yellow one (Forecast Line); note that the difference is that *Forecast Plus MAD* line has been moved up by adding a 1.0 MAD factor to the forecasted values. The standard deviation on the demand's random component is considered to be 1.25MAD, so this Safety Inventory is related to a protection of less than a standard deviation. We propose that this level should be set qualitatively by the analyst according to the Supply Chain's inherent characteristics.

Using this criterion, it is possible to set the Safety Inventory of the Distribution Plan. Now, it is important to define policies regarding where to keep this Safety Inventory: Should we keep it at each node? Should we aggregate it in a strategic node and pull it according to current demand evolution? The answer to these questions lies within each Strategic Network case and the *postponement* possibilities.

The following figure shows a summary of the Distribution Forecast for August, September, October and November. The Winter's Forecast shown is not altered with any MAD protection factor. This forecast application allows the company's analyst to calculate the Supply Chain's forecast for all the items that must be Distributed along the network's nodes.

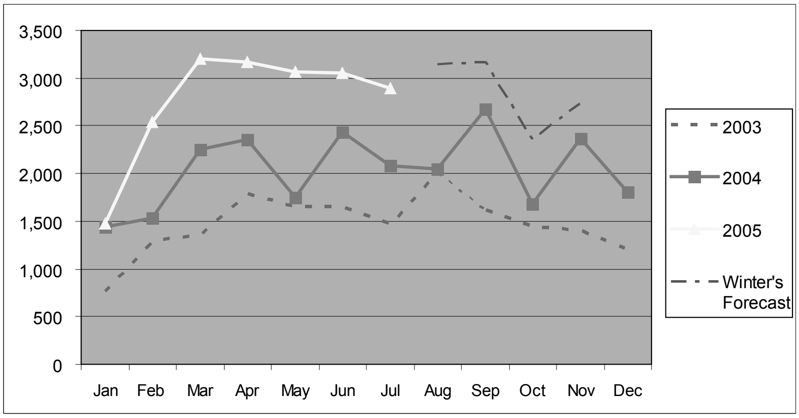

Figure 5. Basic Distribution Network. Winter's Method Forecast for C_a node.

Another important remark regarding the Simple Distribution Network, is that Forecast can help to define the *Pull-Push* Distribution boundary. In this case, the Push Method can be used to send product to each node according to the forecasted needs (since this demand has some degree of certainty and this allows to profit from the Transportation Economy of Scale). Pull Methods can be used to handle the uncertainty demand (MAD) and pull stock from other nodes. Increasing the forecasting effectiveness for each node minimizes overstocking in certain nodes and stockouts in others, since product allocation within the Basic Distribution Network will be more effective.

Using the Basic Distribution Network as a basis, we can jump into conclusions when analyzing Multiproduct Distribution Networks. Multiproduct Distribution Networks are similar to the Basic Network but its configurations change since S supplies different products (x,y,z,...n) to each one of its C_i's, which makes Networks much more complex. Please refer to figure #6. When forecasting the Multiproduct Network, it is possible to use the same forecasting procedure already presented; but when planning the Transportation Plan, it is important to take into account that Transportation now should consolidate different products fostering the economy of scale of the trip.

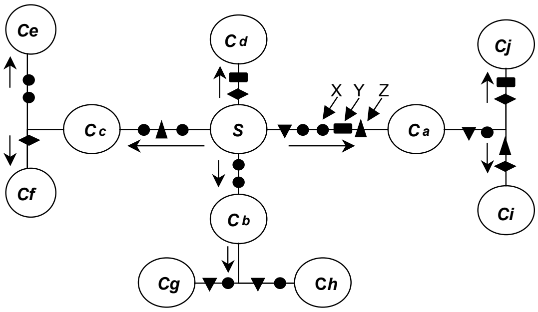

Figure 6. Multiproduct Distribution Network.

The Strategic Planning for a Multiproduct Distribution Network is much more complicated since this Network has to take into account Multi-Relationships among the multiples Si and Ci and different products (x,y,z,…n). At the same time, these S_i actors play the C_i roll for other actors and vice-versa. These relations will be discussed later.

Quantitative Forecasting methods are not enough for Multiproduct Networks. Qualitative Methods can improve the Forecast efficiency since they include predictions based on expected future facts (as per Carranza (2004), it is necessary to use *forward information*) not included in the historic information, for example: new markets or customers. The Qualitative and Quantitative Methods interaction will be presented in the Manufacturing application that follows; a future study branch will be how to integrate the Qualitative Methods in the Distribution context.

MANUFACTURING FORECASTING

Quantitative Methods can be automated, since it is possible to use computers to work out the Forecast for many products. Qualitative Methods are more difficult to implement since the expert criterion should be heard and this is a time-intensive process. Another important factor to consider when forecasting is the aggregation level, since it is easy to work out a Quantitative Method for a SKU (Stock Keeping Unit) level, but it is almost impossible to do so using a Qualitative Method (because of the large quantity of SKU's in the multiproduct scenario, which results very difficult for humans to manage). Nevertheless, the expert criterion is easy to take into account for a higher aggregation level (family level, market level, etc…). According to Bowersox *et al* (2002) and Frazelle (2002), it is important to integrate and rationalize top-down and bottom-up forecasts with human intelligence. During our application in the Distribution context, we have realized the importance of considering "qualitative input". For this reason, we have included this consideration within the Manufacturing context.

Manufacturing is the Supply Chain's source; it feeds product to the chain and makes possible the Distribution process afterwards. Manufacturing increasingly faces the product proliferation phenomenon in terms of demand and product diversity. This proliferation has made difficult to match the product's supply and demand, especially since factors such as strict customer needs, lead time reductions requirements, life cycle reductions, globalization and obsolescence risk increase due to emerging technologies and competition proliferation that have made this match harder than ever. Since Manufacturing is the Supply Chain's source, it has to be strictly planned in order to guarantee product availability along the Chain.

Some techniques have already been developed in order to counterbalance this proliferation phenomenon; among the most popular we have "manufacturing postponement" and "logistics postponement", as per Bowersox *et al.* (2002). These techniques are based

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on *"Pull"* principles. Nevertheless, most of the companies feel the environment's pressure in terms of a great dependence of *Push Manufacturing Strategies* (MTP/MTS for example; please note that all Manufacturing Strategies, even MTO or ATO[1] have certain degree of *Push Manufacturing*; as is the case of components procuring) since there is a need to promptly fulfill customer needs and therefore, speculative (forecasted) needs have to be considered in advance in order to manufacture products prior to customer orders (when it is not possible to attain a flexible and capable manufacturing system). This *Push Manufacturing* dependence makes the precision of the Forecasting Process even more critical.

MULTIPRODUCT FORECASTING CALCULATION COMPLEXITY

The complexity of Multiproduct Forecasting calculations relies on internal and external factors. Among such internal factors we could highlight: large quantity of items (SKU's), a big pool of clients, a lot of different family products, new products coming out everyday, products with correlated demand, complementary products, high obsolescence rate due to product characteristics and nature, and so on. All these factors and other manufacturing dynamics must be taken into consideration when the analysts make forecast calculations for each SKU.

At the same time, analysts must take into consideration external factors such as: changing markets, sales risk increases, market expansions, demand oscillations, higher product obsolescence rate due to new technologies, the proliferation of competition, etc. All these factors must be taken into account in the Forecasting Process, especially through the use of Qualitative Methods.

We propose to integrate internal factors and external factors at the same time. A rich source with basic information could be historical sales data; in this data we can find the historic internal factors' interaction and the real demand that the company has faced. Through the study of this data, it is possible to calculate (for each SKU) the demand components such as *Level*, *Seasonality* and *Trend*; using the same analysis that we have already done in the Distribution case. This analysis or technique, also known as "back-casting", as stated by Frazelle (2002), allows us to calculate forecasts using several quantitative methods and then compare its capabilities to predict the demand's pattern in order to choose the best method. Usually this technique is easy to automate since quantitative methods are composed by mathematics calculations. This feature makes "back-casting" a possible method to be used in a multiproduct context since it is easy to calculate forecasts for a lot of SKU's using computational resources. Nevertheless, this method is based on the assumption that future sales behavior could be predicted based on historic sales; in this case, it is understood that the internal and external conditions will be the same in the future, so they will be likely to repeat

[1] MTO or Make-to-Order; ATO or Assembled-to-Order.

themselves and so, we could forecast future relying on the past. This assumption is not totally valid, since it is very likely that conditions will change because of the market and company's dynamics; as is the case of political variables as per Carranza (2004).

This constraint has made us consider the need to incorporate to the forecast calculations factors that could change future demand. Several authors agree with this and state that "in order to improve the forecasts, it is important to obtain forward information" as could read the translation of what Carranza (2004) has stated. In order to attain this integration, we propose to integrate the Quantitative and the Qualitative Methods in their convenient aggregation level.

QUANTITATIVE METHODS

As previously commented, Quantitative Methods decrease calculations times and their complexity in a Multiproduct context. As presented in the Distribution case, we will use five of the most used methods, and we will judge their prediction capability for each product demand pattern based on the measures of forecasting error already presented; please refer to section 2.1 Distribution Forecasting.

We propose to use the Quantitative Methods in a Low Aggregation Level. Low Aggregation Level has to be define for each SKU; we propose to aggregate the SKU's in the lower but convenient aggregation level; for example we can aggregate SKU's in small families that includes similar or related SKU's, or we could aggregate single SKU's (which would be seen as one-member family). We propose to use Quantitative Methods to profit from the historic data related to each low aggregation level and the possibility of individual calculations; we propose to chose the best method that forecasts the product's demand; as is the case of the following figure which present a coordinate for Winter's or Holt's Method as the chosen method for a certain SKU aggregation level. After all calculations have been completed for all SKU's, all these results are considered together as one coordinate (SKU aggregated). Note that Quantitative Methods could be used in Higher Aggregation Levels, but we propose to use them in Low Levels; see next figure.

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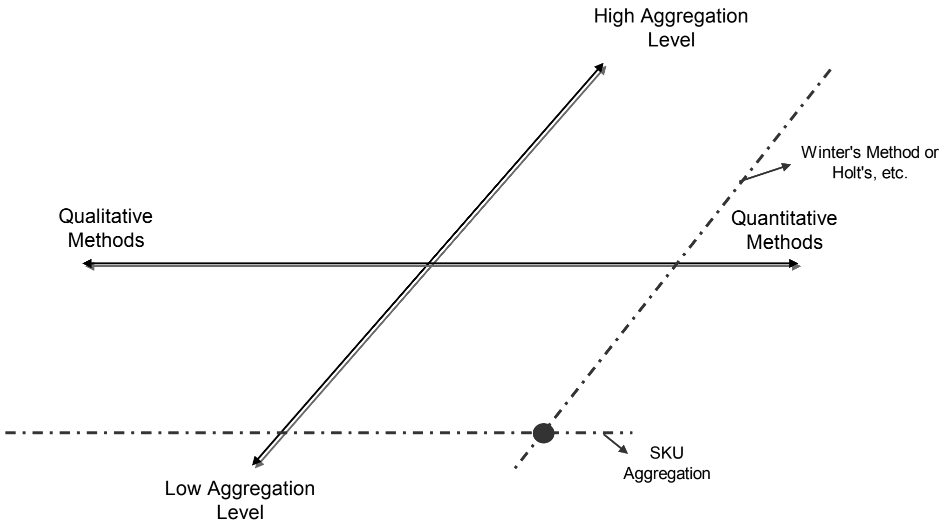

Figure 7. Quantitative Methods and Low Aggregation Level in the "*Method Category-Aggregation Level* Matrix".

QUALITATIVE METHODS

Within the "*Method Category-Aggregation Level* Matrix", we propose to incorporate subjective variables to the forecast calculations at Higher Aggregation Levels. The subjective factors that are incorporated through Qualitative Methods include the manager's intuition (intuition developed based on the manager's experience and "know-how"), previous knowledge of variables that will affect the demand's level (for example: temporary offers, temporary product importation that will compete with the company's products, future market conditions, etc.), and others.

Expert criterion allows the analyst to incorporate his intuition into the forecast in a subjective manner for future demand. This criteria incorporates factors that will affect the future and that perhaps have not impacted sales during historic sales, therefore it permits to consider trends that would not be taken into account by the Quantitative Methods, which base their decision only on historic data. Among the most popular Qualitative Methods, we can highlight the following: a. Opinion Jury, b. Commercial Personnel Proposition, c. Delphi's Method, d. Market Research, and others as presented in Heizer *et al.* (2001).

Within a Multiproduct Manufacturing frame, it is more feasible to consider the expert's criteria in Higher Aggregation Levels and in monetary terms (revenues). It is very difficult for a Sales Department or for a Manager to estimate a forecast with certainty for every single SKU. Nevertheless, when forecasting SKU groups or even product families, qualitative forecasting is easier and precise. For example, it is easier for a Sales Manager to estimate global sales of 4 million dollars and it is very likely that this forecast become precise since the expert knows his company's sales behavior; his expert knowledge allows him to jump into subjective predictions related to multiples variables and factors. These predictions are truly difficult to obtain via mathematical models and its numerous relations that are hard to represent and justify mathematically speaking (especially since it represents complicated and time-consuming tasks). As commented by Silver (1985) there is a relationship between the method that has been used and the aggregation level; expert criteria is essential for the aggregated midterm forecasts. The following figure shows the two coordinates presented at the moment, as is the case for Qualitative Methods which are showed in High Aggregation Levels (Global Aggregation).

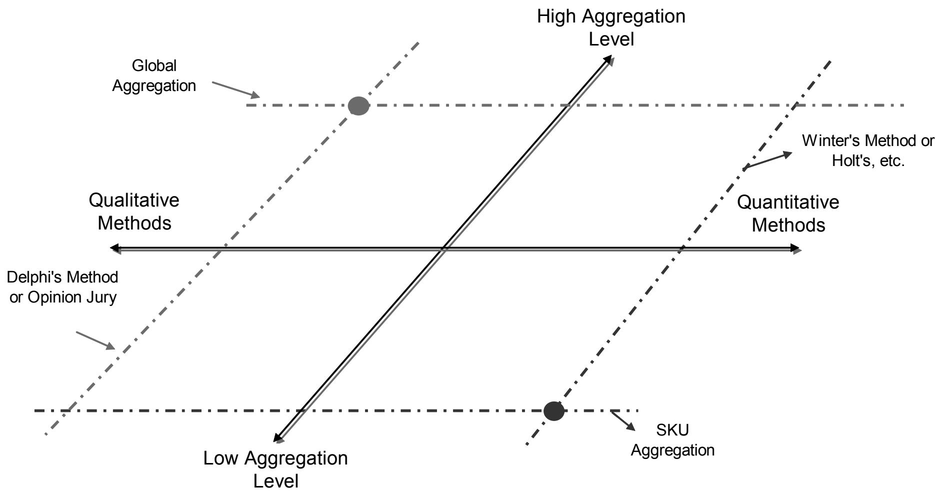

Figure 8. Qualitative Methods and High Aggregation Level in the "*Method Category-Aggregation Level* Matrix".

INTEGRATION OF QUANTITATIVE AND QUALITATIVE METHODS

In figures 7 and 8, we can recognize the coordinate "method category-aggregation level" concept within the matrix. Each of these coordinates suggests that each method is convenient to be used at a certain aggregation level; convenience that we have already discussed in terms of precision and calculation feasibility. This concept allows us consider the possibility of playing with several coordinates and integrate its results in order to achieve better forecasts. In this case, we propose to profit from the different advantages regarding each one of the coordinates and integrate them.

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In order to conceptualize this integration, we propose to create the "Integration Constant Axis (Φ)" in the matrix; this axis integrates the two coordinates. The "Integration Constant Axis (Φ)" presents the infinite possible integration combinations between these two coordinates; please refer to the next figure.

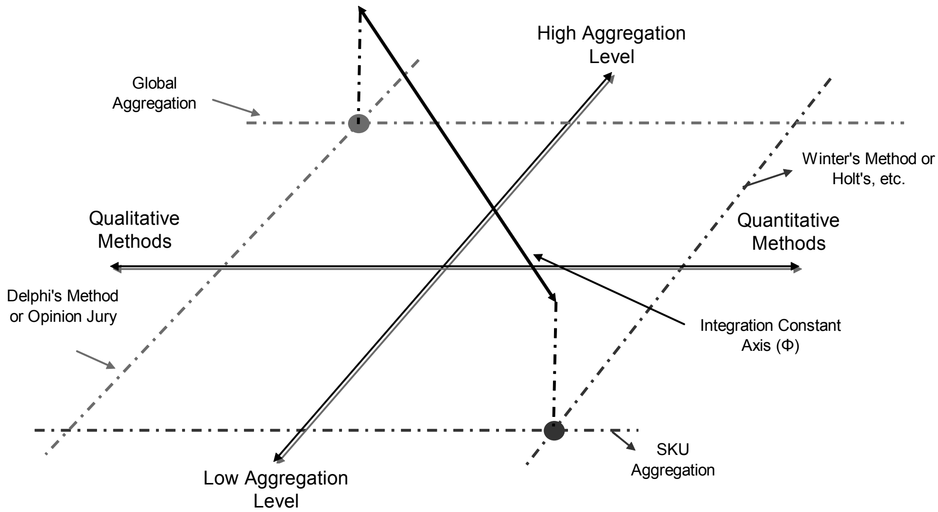

Figure 9. "*Method Category-Aggregation Level* Matrix" and the "*Integration Constant Axis* (Φ)".

Once the "Integration Constant Axis (Φ)" is drawn, it is necessary then to determine the constant value that better integrates both coordinates. When defining Φ we propose to use qualitative criteria using the expert opinion regarding the economic context where the company lies; the more stable the market is (this is the more stable the historic data is and the more it is expected to be in the future), the more reliable the model should be to the quantitative coordinate, since quantitative is based on the historic; the more unstable the market is, the more reliable the model should be to the qualitative coordinate; Φ should be biased accordingly. We also propose to qualitatively modulate Φ based on the results of the calculated forecast; In other words, based on the calculations result, we propose to validate the chosen Φ's value. We can see a potential Φ's value in the next figure.

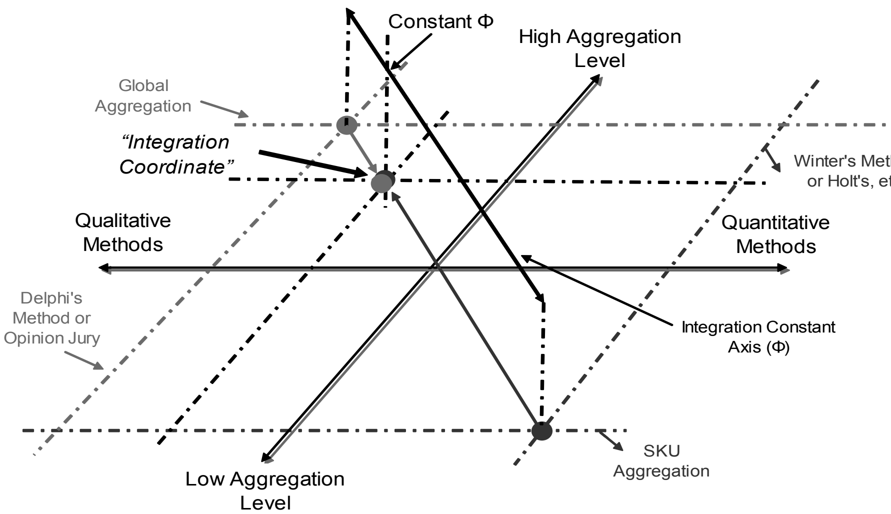

Figure 10. "*Method Category-Aggregation Level* Matrix" and the *Constant* Value (Φ)".

Note that this integration ends up with a new coordinate, the "Integration Coordinate". This new coordinate represents a new forecast that is formed by a new component along the Aggregation Level Axis and a new component along the Category Method Axis. In practice, this concept is quite interesting since it is possible to profit from the Qualitative Methods calculation easiness (in low aggregation levels) and to integrate the results of Qualitative Methods (in high aggregation levels and in terms of revenues/sales). This concept allows us to integrate the Top-Down and Bottom-Up concepts as Frazelle (2002) suggests. As stated by Bowersox (2002), Bottom-Up methods develops SKU forecasts and then builds them into an aggregation demand projection; The Top-Down approach develops a global forecast and then spreads the volume at a SKU level based on historical patterns.

PROPOSED CALCULATION ALGORITHM

Based on the conceptual frame already presented, we present a calculation algorithm.

BOTTOM UP CALCULATION

As already discussed, the low aggregation levels will be defined in terms of "SKU families" or F_{sku}'s; F_{sku}'s should be chosen based on criteria such as complementary products (products that complements each other in terms of demand), demand correlation, demand substitution, and the convenience of aggregating products in order to improve forecast's precision and calculation easiness. F_{sku}'s could include several SKU's or even be composed of a single SKU. The general idea is to determine little families, that because of product similarities, it is convenient to aggregate in a single family. For example, in the case of a forecasting process for a Supermarket, it is convenient to calculate as a family the forecast for products with similar behavior such as is the example of sodas; in this case we can get a global forecast and later on decompose it according to the historic data sales percentage of each soda brand. In this case, we use aggregated forecast to counterbalance the fact that certain customers search to buy one *soda*, and that it could be any of his preferred brands (product substitution; complementary products). Determining F_{sku}'s is still considered as a low aggregation level, since if we compare an F_{sku}'s within the multiproduct context, we realize that this aggregation is small if we compare it with the total SKU's quantity in the multiproduct context.

Once we have defined the F_{sku}'s we "back-cast" the forecast (as we did in the Distribution case showed in this article). We will have the Quantitative Method that adjusts the best to each F_{sku} demand's pattern, this will allow us to find the best forecast for each F_{sku} (we propose to call this forecast FOR_{Fsku}). Once FOR_{Fsku} has been calculated we will decompose it accordingly for each SKU. In this case, this decomposition will be based on the SKU's historic weight or historic percentage within the SKU family (F_{sku}). In order to do this calculation we propose the following formula:

$$wf_{sku} = \frac{\sum D_{sku}}{(\sum D_t)} \qquad [1]$$

where:
wf_{sku}: SKU's demand weight factor within the SKU family (F_{sku}).
D_{sku}: SKU's historic demand.
D_t: SKU family's (F_{sku}) total demand.

Once we have calculated every wf_{sku} we calculate the forecast for each SKU (we propose to call it FOR_{sku}) with the following formula:

$$FOR_{sku} = FOR_{Fsku} \cdot wf_{sku} \qquad [2]$$

where:
FOR_{sku}: individual SKU forecast.
FOR_{Fsku}: SKU family's (F_{sku}) forecast.
wf_{sku}: SKU's demand weight factor within the SKU family (F_{sku}).

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In this moment we have the forecast (FOR_{sku}) for each SKU that composes the SKU family (F_{sku}). This procedure that we have already presented has to be done for each SKU that is manufactured in the company. In the case of new products (new SKU's), in which no historical data is available, FOR_{sku} will be calculated using the most convenient method (for example: through a qualitative method or simply extrapolate a forecast from an existing similar product). This calculation will be not presented here and will be considered as a future investigation to incorporate in our model.

Once we have all the FOR_{sku}'s we calculate the monetary aggregation of these forecasts; we will call this aggregation $AFOR_{sku}$ (SKU's Forecasts Aggregation). $AFOR_{sku}$'s calculation follows this formula:

$$AFOR_{sku} = \sum_{1}^{n} FOR_{sku} \cdot \rho_{sku} \qquad [3]$$

where:
$AFOR_{sku}$: SKU's Forecasts Aggregation in monetary terms.
ρ_{sku}: SKU's selling price for each one of the n SKU's.

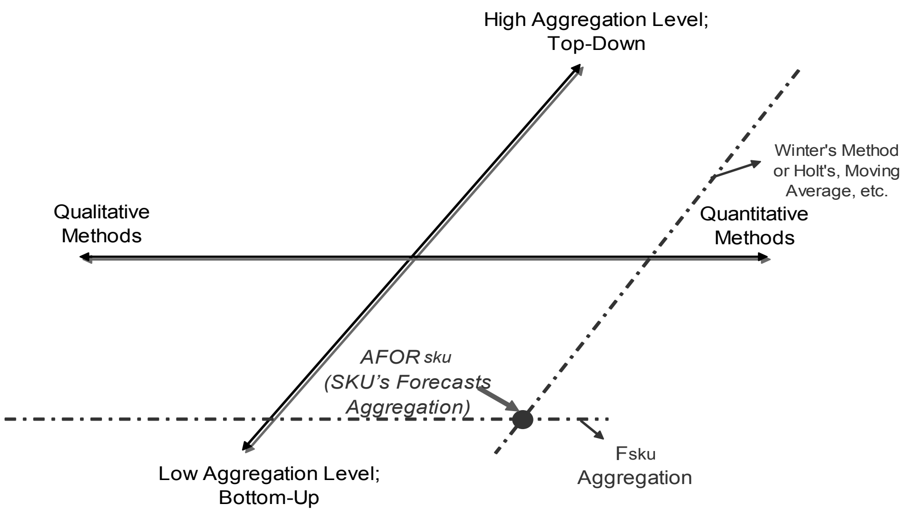

Figure 11. Bottom-Up Calculation and $AFOR_{sku}$. "*Method Category-Aggregation Level* Matrix"

TOP-DOWN CALCULATION

Once we have set $AFOR_{sku}$, we proceed with the Top-Down Calculation. As stated before, this calculation will consider the use of Qualitative Methods. In our application case, the methods chosen to estimate global forecast were: Opinion Jury, Commercial

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Personnel Proposition and Market Research. This estimation was done in terms of revenue and globally speaking (all SKU's aggregated); note that in our application case, managers and experts had the expert criteria to estimate forecast, globally aggregated and expressed in monetary terms (since they have built their *know-how* during years analyzing global revenues, not product units).

The more decomposed the Qualitative estimations, the more precise the forecast could be; but, a higher amount of macro-families result in a more expensive forecast, since Qualitative Forecasting is an intensive time consuming activity (in man-hours). Qualitative Forecasts go with higher aggregation levels, so this is another constraint to consider, since executives feel comfortable guessing for higher aggregation levels and not in lower levels; this is what we call aggregation level trade-off. It is not an objective of this article to present how to calculate forecast with Qualitative Methods, but to show how to apply them.

Once the global estimation has been made (we will call it Global Forecast or G_{FOR}), we will include it in the *Method Category-Aggregation Level* Matrix; please refer to the next figure.

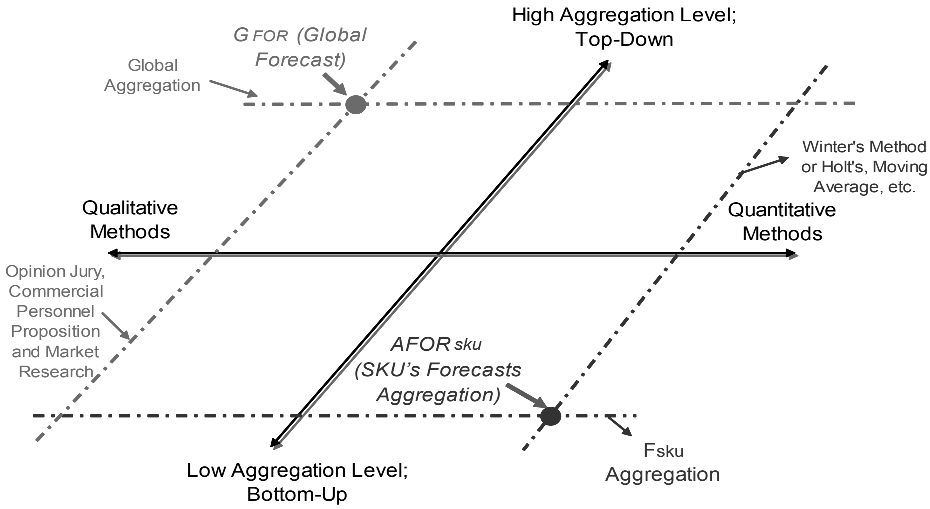

Figure 12. Top-Down Calculation and G_{FOR}. "*Method Category-Aggregation Level* Matrix"

BOTTOM-UP AND TOP DOWN INTEGRATION

Once we have the $AFOR_{sku}$ and G_{FOR} coordinates, we proceed to integrate these two along the "Integration Constant Axis (Φ)". This integrated coordinate will be called Global Integrated Forecast or G_{IFOR}. In order to integrate these coordinates we propose the next formula:

$$G_{IFOR} = AFOR_{sku} \cdot (1 - \phi) + G_{FOR} \cdot (\phi) \qquad [4]$$

We will present a G_{IFOR} using an Φ=0.95 in the following figure:

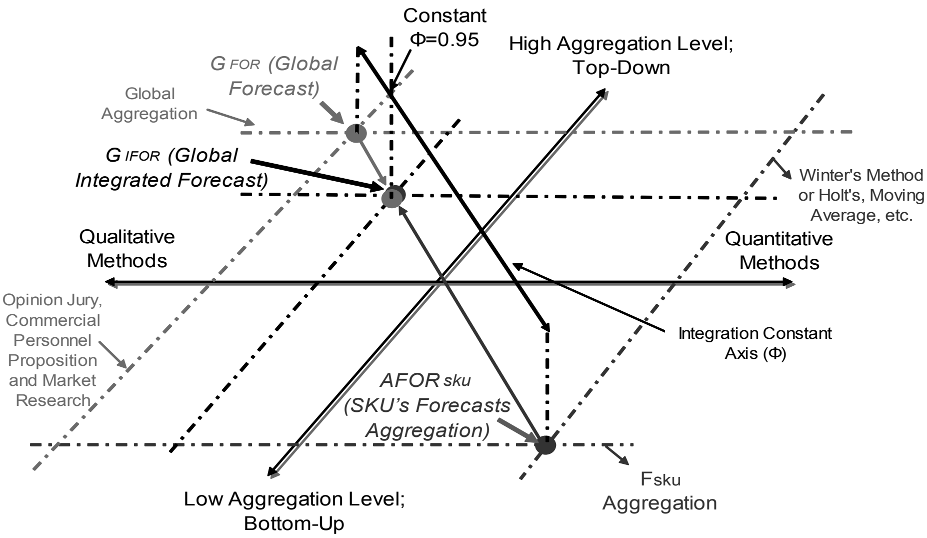

Figure 13. Bottom-Up and Top-Down: G_{IFOR} coordinate. "*Method Category-Aggregation Level* Matrix"

Now, the Global Integrated Forecast (G_{IFOR}) must be decomposed in individuals SKU Integrated Forecasts (or $IFOR_{sku}$'s). In order to have this G_{IFOR} decomposed we propose the following formula:

$$IFOR_{sku} = FOR_{sku} \cdot \left(\frac{G_{IFOR}}{AFOR_{sku}} \right) \qquad [5]$$

ALGORITHM APLICATION

Once we had the algorithm and its equations, we proceeded to apply it to a Manufacturing Enterprise that produces over 250 different finished products (SKU's). The model was run using the historical data related to 3 years of sales history and proceeded to forecast a six month period (from October 2005 to march 2006).

We started to set the different SKU's families (F_{sku}'s) and to "back-cast" its future sales with Quantitative Methods; according to equation (1) and (2) we calculated FOR_{sku} for all of the 250 SKU's. Later on, using (3) and a global level we calculated $AFOR_{sku}$. Using Qualitatives Methods and higher aggregation levels, we defined G_{FOR}. Using (4) we calculated G_{IFOR} and then applying (5) we obtained $IFOR_{sku}$.

When using (4) it is necessary to define the Φ's value. In our case we did set it as Φ=0.95 since expert criteria led us there because of the economical context of the company and its economical expectative; since the economical context has been changing (unstable), managers think that historical data should have little impact in the global prediction and qualitative methods should have more impact; note that even when Φ's value gives $AFOR_{sku}$ light weight, $AFOR_{sku}$ dictates the $IFOR_{sku}$'s sales curve form when using (5).

Among the global results of the algorithm applied to the enterprise we have an average error decrease from 80% for the $AFOR_{sku}$ to 6.2% for the G_{IFOR}. On the other hand, it is logical to think that when comparing G_{IFOR} error to G_{FOR} error (the 6.2% error for the G_{IFOR} to 2.9% error for the G_{FOR}), G_{FOR} has a smaller error due to its global aggregation level. Nevertheless, note that G_{IFOR} allows us to smooth the possible error related to the qualitative forecasting since it considers sales' history weight; even if error is slightly bigger than G_{FOR}, G_{IFOR} allows us to "hear" the historic demand pattern and include it in the forecast's calculation.

In the Manufacturing context, the forecast decomposition plays an important roll since it is critical for the planner to know the forecasted or estimated quantities for each SKU. So, in this sense, decomposing G_{IFOR} into $IFOR_{sku}$ is of great value, since this is useful data for the planner. Even if we loose forecast precision, due to a decrease of our aggregation level, decomposing is a must for the Manufacturing operation.

Regarding the algorithm's results at a decomposed SKU level (this is comparing $IFOR_{sku}$ level vrs FOR_{sku} level), we propose to analyze both forecasts in monetary terms. In order to evaluate the convenience of this algorithm we will contrast the cost of using the $IFOR_{sku}$'s with the cost of using the FOR_{sku}'s. In order to contrast these two forecasting methods, we propose to quantify the value of each method in terms of cost. Each method will be compared to the real sales for the forecasted periods; please note that at this moment we know the exact sales quantities for the forecasted period (October 2005-March 2006). To quantify the cost of each forecasting method we propose to consider the over-forecasting cost (overstocking) and the under-forecasting cost (stockout). We propose to consider the overforecasting cost as the monthly carrying cost, and the underforecasting cost as the stockout cost related to the monthly lost sales (in terms of the lost earnings or lost margin related to the products not sold). This procedure helps us to evaluate forecasting methods considering the Manufacturer's real situation (in terms of inventory carrying costs and sales loss).

So, assigning the positive forecast error to MCCR and the negative error to the SoCR we have:

$$FMC = (pe_{sku} \cdot (CCMR) + ne_{sku} \cdot (SoCR)) \cdot \rho_{sku} \qquad [6]$$

where:
FMC: Forecasting Method Cost.
pe_{sku}: positive error in units for a certain SKU.
MCCR: Monthly Carrying Cost Rate.
ne_{sku}: negative error in units for a certain SKU.
SoCR: Stockout Cost Rate
ϱ_{sku}: SKU's selling price.

After comparing both costs, we discovered that the algorithm yields an average cost reduction comparable to a 6.6% of the earnings margin of the product (6.6% out of 18% as the earnings margin), which is quite attractive. Note that the company's MCCR and SoCR values used were around MCCR= 1% and SoCR=18%.

As presented, this algorithm allows the Manufacturer's analyst to calculate the Supply Chain's forecast for all the items that must be fabricated in order to be, later on, Distributed along the Supply Chain in order to be available to final customer. As presented, this case considers a global aggregation for the whole enterprise when applying Qualitative Methods; it is evident that the same algorithm can be applied to Multiproduct Environments but at a lower global aggregation level. In our case, 250 SKU's permitted us to aggregate them in a global prediction. When using this same principle, but in a company with a larger quantity of SKU's, we could decompose the totality of products into strategic ensembles that could be treated as targets to calculate G_{FOR} and $AFOR_{sku}$ and later on get a G_{IFOR}; in this sense, we would use the "*Method Category-Aggregation Level* Matrix" concept to each of the strategic ensembles within the enterprise, and later on aggregate its results; we could see it as a "company within a company" treatment.

BUSINESS STRATEGY AND FORECASTING

Through the Distribution and Manufacturing Process, companies should materialize its Business Strategy, since product availability (in terms of quantity and place) is essential to satisfy Customers. Distribution is seen as the latest step, supplied by the Manufacturing step.

Forecasts can be used as a tool to produce and allocate product to each Customer. According to Carranza (2004), forecasting processes are much more effective when they are performed in collaboration with the entire Distribution Network than when they are individually calculated by each S and C actors; they can be used to strengthen the Supplier and Customer relationships. This collaboration is not natural between members, since it consumes time and energy to do it. Although it is difficult, some businesses have realized about its importance, since improvements in Forecasting and

Planning have had significant success, as stated by Chopra *et al* (2004).

We propose that the implementation of a collaborating forecast is related to the Negotiating Force of the S and C actors. This force difference will also determine Supply Policies. The following are three types of possible relationships based on the different Negotiating Force between Suppliers and Customer when negotiating Supply Policies:

i. Supplier Negotiating Force Superiority over its Customer.
ii. Customer Negotiating Force Superiority over its Supplier.
iii. Supplier and Customer Negotiating Force Parity.

NEGOTIAGING FORCE SUPERIORITY OVER ITS CUSTOMER

In this case, the Supplier will set the guidelines according to what is convenient for him, for example:

- Supplier will control *Lead Times* by pushing his customers to place purchase orders with as much possible time in advance. Doing so, Supplier will increase the precision of his forecast (since he will produce "make-to-order"). This practice will help him reduce his operative costs.
- M.O.Q's policies (Minimum Order Quantity) will be implemented so that the Supplier could profit from the production and transportation economies of scale. Suppliers sometimes pay for the transportation cost as a *Customer Service Policy*, but their main objective is to force the customer to place M.O.Q's Purchase Orders. All these policies should be tacitly accepted by the market and customers; otherwise they become counterproductive as a risk of potential market loss.
- Supplier will try to push to its Customer the Economical Inventory Risk related to Forecasted Sales; S will try to push the product to C at the earlier possible moment.
- Supplier will not be worried to develop and to train its Customers with Forecasting Tools and Supply Policies in order to optimize the Chain. The interest is unilateral and S makes decision aiming his local optimal point. Sometimes, this policy could yield short term profits but later on long term losses (so is the case when the Supply Chain gets saturated due to supplier and customer communication problem; the *Beer Game* is a parody related to this problem as evoked by Carranza (2004). These communication problems could be very expensive for Suppliers since its Production Capacity has to be changed accordingly.
- Supplier S will offer a slightly better Customer Service Level in terms of his competitor's Service Level. The Strategy would be to differentiate from competitors but not completely exceed them. This is how S will avoid his Customers to place purchase orders to the competition. For example, a Customer will prefer a Supplier that offers him the possibility to demand partial and

immediate shipments, with shorter lead times and the same quality (this is an example of a differentiating strategy). Please see Figure #14.

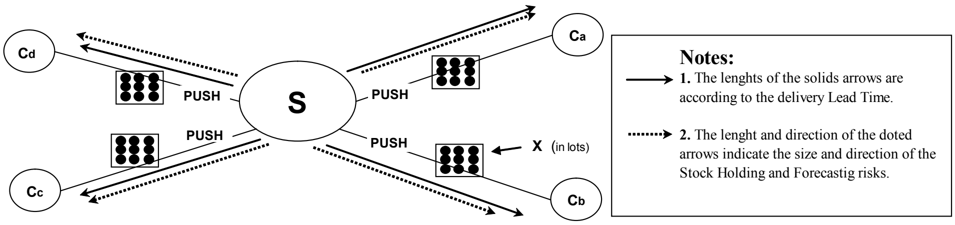

Figure 14. Basic Supply and Distribution Network: Supplier Negotiating Force Superiority over its Customer

CUSTOMER NEGOCIATING FORCE SUPERIORITY OVER ITS SUPPLIER

In this case, the Customer will set the guidelines according to what is convenient for him. For example:

- Customer will prefer his Suppliers to follow *Just in Time* supply policies. Since its commercial advantage allows him to exploit the equation service, the customer will aim to have the product at the Right Time, in the Right Place, and in the Right Quantity (an example could be the supermarket sector and its relationship with its suppliers). Since Suppliers should react immediately, this makes them deal with all the Forecasting and Planning burden. This practice pushes the risks towards Suppliers. *Just in Time* orders are characterized by its small sizes and high frequencies due to short lead times.
- Customer will foster his Supplier proximity in order to guarantee its product supply and flexibility even under strong demand changes. In some cases, C will foster S physic proximity in order to minimize the transportation time (classic example of the automobile industry).
- The economical inventory holding risk will be pushed toward S. It is a frequent practice for the biggest C's, to make its Suppliers to carry a fixed physical Safety Inventory in order to guarantee an agreed Service Level (this is usually done under economic penalty conditions for not fulfillment cases). This penalty pressure makes the Supplier to have a bigger need for Forecast accuracy or higher Safety Inventory levels.
- Another Suppliers strategy is to guarantee a Customer Portfolio that allows S to supply many other customers with reasonable size (as the C_d, C_c and C_b case in figure #15). This allows S to equilibrate the higher economic pressure that the biggest C puts on him (see below figure).

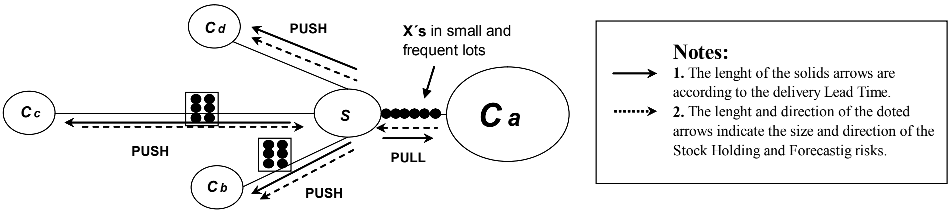

Figure 15. Basic Supply and Distribution Network: Customer Negotiating Force Superiority over its Supplier

SUPPLIER AND CUSTOMER NEGOTIATING FORCE PARITY

In the case of Negotiating Force Parity, both actors will try to set the guidelines according to what is convenient for them, for example:

- Both actors will be interested in mutual growth.
- Mutual coordination will be aimed in order to set the Supply Policies that works the best.

The Negotiating Force Parity condition could come from many possible sources, for example:

i. **Negotiating Force Evolution through time for one of the actors.** For example: aggressive Customer requirements (costs reductions, shipping conditions, etc.) sometimes make small and medium suppliers go bankrupt, or to "merge" with a stronger actor (or even to sell the company). Later on, the market that these competitors used to own, is absorbed by the strongest "survivor" Supplier who now gains Negotiating Force toward Customers.

ii. **Negotiating Force gains due to a Strategic Advantage.** For example: a big Customer wants to develop a strategic Supplier in order to guarantee his requirements supply such as: quality level, physical proximity, supply flexibility, technological advantage, etc. In this case the Supplier gains Negotiating Force.

FORECASTING AS A COUNTERBALANCE FOR NEGOTIATION FORCE DIFERENCES

These three scenarios highlight the pressure that each actor has. We can compare this pressure to the *Implied Demand Uncertainty* concept since, according to Chopra *et al*. (2004), it "is the resulting uncertainty for only the portion of the demand that the supply chain must handle and the attributes the customer desires". This pressure based on the Implied Demand Uncertainty could also come from the differences in *Negotiating Forces*.

Nowadays we can hear from collaborative planning techniques such as CPFR (Collaborative Planning, Forecasting, and Replenishment); these techniques have been successfully implemented in *Negotiating Force Parity* situations, since both actors are truly interested in mutual benefits, which motivate them to allocate their resources to this project. Chopra *et al.* (2004) shows some of this examples.

In many cases, *Force Superiority* can not be exploited by stronger actors in a sustainable way without considering the long term impact over the weaker actor (especially if the weaker actor can find an advantage in order to be considered by the stronger as a critical strategically speaking actor). The weaker actors could profit from this fact and use it as an argument in order to negotiate and foster teamwork to improve the Supply and Distribution Network.

Our model proposes the importance of using simpler collaborative techniques in the *Negotiating Force Non- Parity* environments; in this sense, the weaker actor requires to improve its products supply management through a forecasting process improvement, as is the case of the Method we are proposing, and therefore reduce its pressure or *Implied Demand Uncertainty*. This improvement can help the weaker actor to counterbalance its Negotiating Force by being proactive with the stronger actor and fostering a collaborative environment to improve the service the weaker offers. We propose that this initiative must come from the weaker actor; a possible tool for weaker actors to reach this is through the use collaborative Forecasting Process.

Within the reality of the Supply Chain, since companies usually have different suppliers and customers, companies play different *Negotiating Force* rolls; in this sense, companies could play the weaker or stronger actor roll depending on each case. When Planning the Multiproduct Supply Chain, it is evident that each company has to concentrate in the most important of these relationships; a Paretto analysis is recommended in this situation.

CONCLUSION

Distribution and Manufacturing Strategic Planning is critical for companies that deal with Manufacturing and Distribution processes. Both processes have to be planned in accordance one with another.

Forecasting processes can be implemented in the Distribution network in order to guarantee product availability by improving the product allocation process within the Supply Chain (within each Supply Chain's node). Forecasting processes can be implemented in the Manufacturing process in order to improve the availability of product to supply the custumer's needs in terms of quantity and place.

When planning the Manufacturing and Distribution processes it is critical to consider the company's position within the proposed *Negotiating Force* frame; the company must understand its position and try to improve it strategically. Customer's or Supplier's pressure can be handled and reduced through forecast as a step to reach collaborative forecast. Since in the Multiproduct context there are multiples customer-to-supplier and supplier-to-customer relationships, each company has to understand which of these relationships represents the critical ones in order to strategically improve them.

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