Proceedings of the World Congress on Engineering and Computer Science 2007
WCECS 2007, October 24-26, 2007, San Francisco, USA

Evolution in Demand Translation in Global Sourcing of Components

K. Senthil Kumar and Prashant Momaya

Abstract — **Sourcing components globally is becoming increasingly common across the automotive components industry. Global sourcing very often results in lower costs traded off against longer lead times. Simultaneously customers demand increasingly customized products with shorter lead time from their Tier-1 suppliers. This has increased conflicts in matching component and customer lead times in the Assemble-To-Order (ATO) environment and resulted in considerable dependency on forecast accuracy to enable on-time-delivery. The use of advanced tools for the Master Production Scheduling (MPS) to control the demand forecast accuracy do not result in improvements to delivery if these controls remain at the aggregate level of product hierarchy. The ability to review the demand accuracy at the lower level of the product hierarchy would lead to improvement in right-first-time on the assembly line and reduce inventory of wrong components. To effectively deal with the global sourcing scenario this paper proposes a Planning Bill of Material (PBOM) model for translating the demand to the component level along with the metrics for measuring and controlling its effectiveness. The paper also lays out a process for managing the demand translation process using the proposed PBOM model. A real life case study to illustrate the use of the model and the process is also presented.**

Index Terms— **Planning Bill of Materials (PBOM), PBOM accuracy, forecast accuracy, forecasting, demand translation, Assembled to Order (ATO), Master Production Scheduling (MPS)**

I. Introduction

Manufacturing organizations are faced with a dual lead time challenge. On one hand the manufacturing OEMs are increasingly participating in global sourcing programs to stay cost competitive often at the expense of having longer lead times for components sourced from the so-called low-cost-countries. On the other hand the customers of these OEMs are demanding lower lead times for their products along with a proliferated product portfolio and short product life cycles.

To balance this lead time difference in the supply chain, the automotive component OEMs operate with the Assemble-To-Order (ATO) strategy, which requires accurate forecasts for controlling the on-time delivery and the inventory cost. Even when they use the latest techniques available, there are too many dependencies to be recognized in order to accurately forecast demand. In general the higher the level of the forecasted entity in the product hierarchy, the lower are these dependencies and the higher is the forecast accuracy. Keeping this in mind the Sales & Marketing functions generally forecast at the product family level to achieve high performance of the forecasting process. It is the master scheduler who translates this high level forecast in terms of both product and time into one that is at a sufficiently low level for Material Requirements Planning (MRP) tools to send the supplier schedules for components. Generally, this translation process assumes the product mix of the past few months, but it is our observation that few organizations tend to have proper review processes to ensure good translation from a high level forecast to end components. This review is the critical link for the making the right parts available to ensure delivery performance.

A. *Demand Chain Challenges in ATO Environment*

The authors have observed that Tier-1 suppliers in the automotive components industry generate forecast at the level of product family in monthly buckets for a long horizon, say 12 months. The customer lead time limits the frozen fence in this horizon for not more than a month but the supplier lead time varies between 0 days for vendor managed inventory (VMI) suppliers and 120 days of some key international suppliers. The forecast accuracy measured in terms of 1 – Mean Absolute Percentage Error (*1-MAPE*), ranges from 70% to 80% at the product family level. However, the demand accuracy at the end product level is as low as 35%. The industry witnesses this as the reason for part shortage in the assembly line and also for the excess and/or obsolete inventory

The features offered to the customers are so varied that it is difficult to control the demand accuracy of each of them and there is little feedback, if any for the master scheduler on the future mix coming out of market intelligence and new product introduction (NPI) programs. Also the changes in downstream demand are so volatile that it is difficult to control the demand accuracy for smaller time bucket in future. These two challenges necessitate a sound mechanism for controlling the translation of the forecast into lower levels to allow good line capacity utilization and prevent high levels of excess and/or obsolete inventory

Manuscript received on July 21, 2007. This work was supported by the Manufacturing Industry Practice, Tata Consultancy Services Limited www.tcs.com

Both authors are Supply Chain Consultants with the Automotive Group of Manufacturing Industry Practice in Tata Consultancy Services Limited

K. Senthil Kumar has working and consulting experience in the supply chain processes of Manufacturing industries such as Aluminium, Automotive Component, Light Engineering, Heavy duty Machinery and Turbines. (phone : 252 437 9496; email: senthilkumar.k@tcs.com,).

Prashant Momaya has research and consulting experience in optimization problems of Manufacturing industries (phone : 252 437 9496; email : prashant.momaya@tcs.com).

B. Literature Survey

Demand planning for ATO environments has been under research from the nineteen eighties. The different methods identified in literature are –.

1) *Modularization [1]*
The bill of material for every model is rearranged with groups of components, called modules. Forecasting and order placement are both carried out at the modular level.

2) *Synthetic bill of material*
The bill of material is built for each product family having common parts and features under it with a percentage for translation of high level demand. There is a variant called 'Sequential synthetic bill' which links the features at various levels according to their interdependency

3) *Heuristics*
The set of end products for the forecasting process is scaled down to a manageable few. These few are then over-planned with intuitive percentages for covering the other products not forecasted.

4) *Hierarchial pseudo bill for non-modular products*
The common parts and features are forecasted with the service level addressing the demand uncertainties of the respective feature.

Though these methods have certain known advantages, some of the problems associated with these methods are –

- There are more number of forecast elements
- Not every mix of modules can be assembled perfectly into a mix of end products without leftovers
- Interdependency of features needs rigorous review especially in case of wide product proliferation
- Unique parts required for the other end products cannot be planned
- No control process for maintaining the percentage
- No control process on the accuracy of the forecast

This paper addresses these problems in the given context of the automotive components industry with a modified structure of the planning bill for controlling the process in a more effective manner.

II. Planning Bill - Model and Measurements

A. Planning Bill of Material (PBOM) accuracy

In the proposed model, the PBOM process translates the forecast from the level of product family in monthly buckets to the level of end products in weekly buckets. Though the input is the rolling forecast for medium term, say 12 months, the focus is on the one, which is frozen with that time period (demand time fence), say 2 months out. Usually, the forecast is frozen for the period of the longest supplier lead time. The accuracy of this process determines the effectiveness of demand translation and can be expressed as the ratio of accuracy of output to that of input as described in (3). This measurement is effective in capturing (a) the capability of building the complete end products resulting from the hits and (b) the bottom-line losses due to inventory resulting from the misses in comparison of forecast against actual demand. The MAPE at end product and weeks is given by

$$MAPE_{p,t} = \frac{\sum_{t=t_1}^{t_x}\sum_{p=1}^{n}\left|\left(F_{p,t} - D_{p,t}\right)\right| \times M_p^{\,S_{p,t}} \times C_{p,t}^{\,(1-S_{p,t})}}{\left(\sum_{t=t_1}^{t_x}\sum_{p=1}^{n} D_{p,t} \times M_p\right)} \tag{1}$$

where each end product, p of the total n products has a forecast F, that is made 2 months out and the actual demand D for the time period from t_1 through t_x weeks, M is its margin value, C its inventory cost for over-forecast in the period t and S is a Boolean with a value *1* for under-forecast and *0* for over-forecast. The MAPE calculation here has been adjusted with the inventory cost and margin loss factors appropriately. The inventory cost is the summation of holding cost for all the parts in the bill of material for the respective end product with lead time greater than demand time fence

MAPE at product family and month T, which is 2 months out from the current month is given by

$$MAPE_{P,T} = \frac{\sum_{P=1}^{m}\left|\left(F_{P,T} - D_{P,T}\right)\right| \times M_P^{\,S_{P,T}} \times C_{P,T}^{\,(1-S_{P,T})}}{\left(\sum_{P=1}^{m} D_{P,T} \times M_P\right)} \tag{2}$$

with the same notation as above, but here MAPE represents the product family P of m families and the month 2, which is the forecast, frozen at this time. This input for the process is not controllable in PBOM process, as it is the result of the upstream forecasting process. The PBOM accuracy is given by.

$$Accuracy_{PBOM} = \frac{\left(1 - MAPE_{p,t}\right)}{\left(1 - MAPE_{P,T}\right)} \tag{3}$$

The control chart on this measure for every product family with the respective pareto on the end products of the family ($B_{P1} = \{p_1, p_2, ..\}$, where B_P is the set of end products, p for the family P) would help to identify the respective product family and/or the end product for control and improvement.

The equation (1) assumes that the components are allocated for each product family, as is the case for a few segments in this industry. However, if there is no allocation which is quite prevalent, the under-forecast elements would need to be adjusted by adding the additional possible build using the excess material from the over-forecast elements till that time period. This adjustment needs an optimization, as given in (4)

$$F_{adjusted,p,t} = F_{p,t} + S_{p,t} \times \min\left(F'_{p,t,q} : q \in Q\right) \tag{4}$$

where each component, q of the total Q components is evaluated for the availability using (5) for $F'_{p,t,q}$

$$F'_{p,t,q} = \frac{\left(\sum_{i=1}^{p}\sum_{j=t-y}^{t} b_{i,q}F_{i,j}\left(1 - S_{i,j}\right) - \sum_{i=1}^{p}\sum_{j=t-y}^{t} b_{i,q}D_{i,j}\left(1 - S_{i,j}\right) - \sum_{i=1}^{p-1}\sum_{j=t-y}^{t} b_{i,q}F'_{i,j}\right)}{b_{p,q}} \tag{5}$$

where b is the quantity of the component, q required for end product, p. The time interval for checking the component availability can go back as far as y months, beyond which the organizations turn the material into obsolete inventory. This adjustment improves the forecast accuracy from its base level in (1) by a few times in most occasions. This is due to the large components in the bill of material for every end product of ATO environment.

B. Decomposition of the PBOM process

To control the PBOM accuracy, the PBOM process can be divided into three sub-processes, namely PBOM reorganization, Product level translation and Time level translation. The PBOM reorganization is a process of grouping the forecasts of product families to keep a limited number of PBOMs for reviewing the product level and time level translation processes. Generally, this is done for the bottom 20% of demand – this means distinct PBOMs for the top contributors to the demand and grouped PBOMs for the lower contributors. In the ideal world, there is one PBOM for every product family, mapped with all the end products of the respective family. Sometimes, there is also a need to split the product family into 2 or more PBOMs to increase the PBOM accuracy. This need is reflected in the review to profile the PBOMs, considering factors such as the percentage of unique parts in the PBOM, the demand variation for end products in that PBOM, the amount of engineering changes and NPI expected and the importance of customers for allocating the material. The product level translation is a process to convert the given product family forecast into that of end products. This uses the product mix in the actual demand of the given horizon to determine the proportion of every end product in a product family called product level attach rate. The time level translation is a process to convert the forecast at the end product level from the previous process to that at the lower time dimension say weeks with the proportion of every week called time level attach rate. Though these processes happen for all time periods of the rolling forecast, the focus is again on the frozen forecast of month 2. The contribution of these processes to the PBOM accuracy can be measured by decomposing the parent metric into Product level attach rate accuracy and Time level attach rate accuracy, as given in (6) and (7)

$$Accuracy_p = \frac{(1 - MAPE_{endproduct,month})}{(1 - MAPE_{productfamily,month})} \quad (6)$$

$$Accuarcy_t = \frac{(1 - MAPE_{endproduct,week})}{(1 - MAPE_{endproduct,month})} \quad (7)$$

These measures allow identification of any error in the translation at the product level or the time level and enable us to address them appropriately.

C. Over-planning requirements

The options or the features of every product family would almost always outnumber the number of end products and the disparate planning for these options will generate "left-over" options. These left over options will result in inventory that can not be used (this inventory would eventually end up as excess or obsolete). In many cases the modification of option level demand is intuitive and does not lend itself to proper measurement and quantification. For this reason the proposed model aims to translate the demand into the level of end products and does not allow over-planning of any one feature over the other to avoid any rise in inventory. The proposed model is used best in combination with component level safety stocks, determined by the statistical methods. This model recommends (a) segregating the marketing feedback into end product specific adjustments and feature specific adjustments, (b) implementing the product specific ones as a part of the attach rates with appropriate modification on the calculated value from the forecasting techniques and (c) routing the feature specific adjustments to the safety stock review process so that the demand translation problem is not burdened with subjective inputs.

III. Formulating the Demand Translation Problem

The problem of product level demand translation can be expressed as follows.

Forecasting the product level attach rate for every end product with the data of its actual proportions of the past demand as well as the past forecasted attach rates subject to the constraint of summation of such attach rates across a product family being equal to 100%

$$\sum_p R_{p,T} : p \in B_P = 100\% \quad (8)$$

where *R* is the forecast attach rate for end product *p* and month *T*

For this the short term forecasting techniques can be used. The author has used the following.

(a) Exponential smoothing,

$$R_{p,T} = \alpha \times A_{p,T-L} + (1-\alpha) \times R_{p,T-L} \quad (9)$$

where *A* is the actual attach rate per demand data for the period *T-L*, which is L months out from the period *T*; *L* is the frozen forecast time fence and $\propto$ is the smoothing constant, $0<\propto<1$

(b) Moving average with weights

$$R_{p,T} = \sum_{k=0}^{l} W_k \times A_{p,T-L-k} \quad (10)$$

where *l* is the horizon for the weighted average and *W* is the weight for each month in this horizon

This should be followed by a sensitivity analysis to identify the best method and the most accurate value for the parameters with the objective of maximizing the product level attach rate accuracy in (6). It is recommended to have a tool that carries out this analysis through a goal programming model on the function in (6) and the constraints from (8) to (10). Owing to the frequent changes in the market requirements, it is also recommended that this analysis be repeated in regular intervals.

The time level translation problem is also carried out in the same way because even here there is a distribution of forecast from a large bucket of 1 month into many small buckets of weeks just like the distribution from product family to end product in the product level translation.

The demand translation from the high level to the low level of product and time mitigates the risks of generating forecast at the low level. However, the attach rates forecasting techniques, used for this translation process are based on the historical composition of the product family and the historical movement of individual end product as well as the commonality of components of end products within the given product family. If the PBOM accuracy is not controllable to reach the required improvement using the forecasting techniques, the product family might need to be split into two or more PBOMs and the forecast for these PBOMs might need to be either generated or derived from that of the parent product family. This is carried out using the PBOM reorganization process, in which (a) the product families with poor PBOM accuracy and high demand volume are identified and (b) the end products of these product families are reorganized into various PBOMs to minimize the factors contributing to the noise, preventing the improvements in attach rate accuracy through the forecasting techniques. These factors have been identified as follows.

1. Demand variation – Higher the variation, the lower is the dependence on the previous time bucket and the lower is the accuracy of short term forecasting techniques for attach rates
2. Proliferation of end products – Higher the proliferation, the higher is the chances of variation for the individual end products
3. Unique components (components required in only one end product of the given product family) – Higher the unique components in the end product, the lower are the chances of the availability of excess material from over-forecast end products and the lower is the product level attach rate accuracy
4. Priority customers (if materials are allocated to the customers in planning and execution) – If there is material allocation for priority customers, the end products for these customers is grouped separately under one PBOM to avoid the shared planning of these materials with the requirements of the other customers

This "Aggregation Noise" is a function of the factors, listed above by converting each of them into a comparable percentile with the worst value in the given population of product families.

Aggregation noise =

$$Noise_{Aggregation} = \frac{CV_P}{\max\left(CV_P : P \in m\right)} W_a + \frac{UC_P}{\max\left(UC_P : P \in m\right)} W_b + \frac{PP_P}{\max\left(PP_P : P \in m\right)} W_c + \left(IC_P \times W_d\right) \tag{11}$$

where CV is the coefficient of variation of product family demand, defined as the ratio of the standard deviation to the average, UC is the percentage of unique components in the product family, defined as the ratio of the number of components, required in only one end product in the product family to the total number of components, PP is the product proliferation in the product family, defined as the number of end products and IC is the priority customers in the product family, defined as *1* if even one end product is supplied to 'important customer' and *0* otherwise. Important customers are generally identified by the kind of business relationship between the supplier and the customer and may result from lead time agreements between the two. W_a, W_b, W_c and W_d are the weights assigned to these factors, defined according to the business requirements in a scale of 0 to 1.

After reorganizing the PBOM structure, the attach rate calculations for both product level and time level are redone to determine the new PBOM accuracy. If the new value is found to be satisfactory, the PBOM structure, the forecasting technique and the parameters are retained till the next review for the demand translation into lower product and time level.

IV. Case Study

A. Demand accuracy problems

The organization in this case study had a number of product families with the demand distribution as depicted in Fig.(1).

Among these product families, about 5500 options were offered to the customer, with a range of less than a hundred to more than a thousand per product family. The end products, configured with these options were about 700 per annum, which constantly changed with the release of new options. The organization ran the assembly line in an ATO environment by sourcing the components from global suppliers with long lead times. The organization generated a forecast at the product family level using an advanced forecasting system. As the purpose of the forecast is to bridge the customer lead time and the supplier lead time, the median values of which are 1 month and 2 months respectively, the measurement of forecast accuracy 2 months out was significant. Fig.(2) represents the accuracy, generated at the month level for the top 3 product families.

Even though the average accuracy was around a healthy 75%, the assembly line throughtput, ranged from 400 to 500 pieces a month on an installed capacity of 800 pieces per month along with a poor on-time-delivery performance. Analysis showed that the material shortage for assembly did not reduce even though the supplier delivery performance was impressive at 88%. The demand chain transformation project aimed at improving the forecast accuracy at the lower level of product and time with the consequent improvement in the right first time completion of assembly.

B. PBOM process

The existing PBOM process was to distribute the monthly forecast at product family level evenly into weeks and then translate into the features, called options with option level attach rates. The attach rates were calculated with the average product mix data for the past 4 months and the future 2 months. Also in this process, the option level accuracy was measured as 64% as shown in Fig.(3).

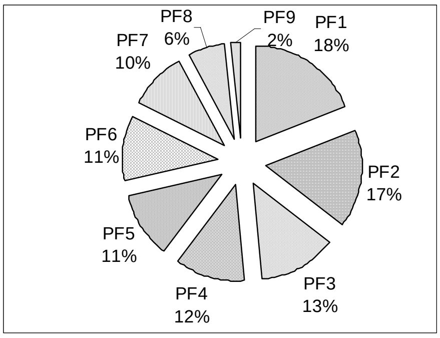

Figure 1 : Product Family Demand

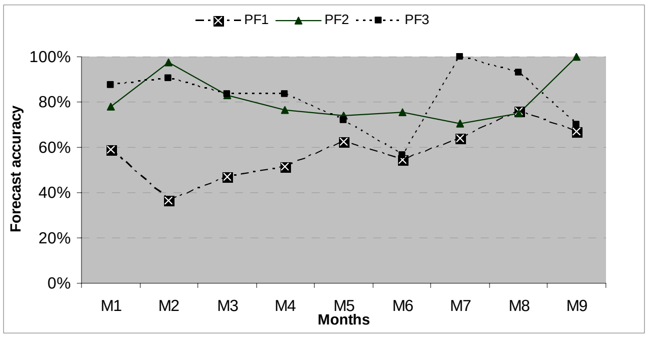

Figure 2 : Forecast accuracy for the top 3 families

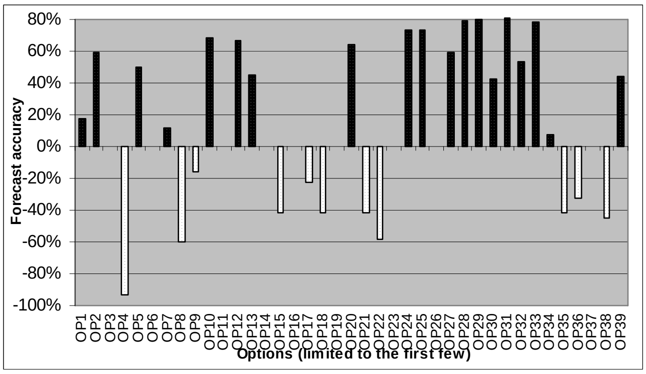

Figure 3 : Option level forecast accuracy

However, this option level accuracy could not be converted into the number of right first time build in the assembly line. It was difficult to find out how much of the 75% right forecast, made at the product family level were realized with material availability in the assembly line Right First Time. Also, it was difficult to find out which option was the bottleneck in improving the Right First Time and how to effect an improvement for that option.

C. Attach rate calculation with new model

The forecast accuracy at the level of end products and weeks was analyzed according to the new model to identify the best method and the parameters for forecasting the attach rate for product level. This analysis used equal weights for over-forecast and under-forecast errors in terms of margin cost and inventory cost in (1) and (2). This reflected the organization's requirements of minimizing the rise in inventory being as important as that of building the assembly in time. After the analyses of all the forecasting models for attach rate forecasting, Exponential smoothing was selected with smoothing constant equal to 0.75. The large proliferation of end products, ranging from 15 to 150 per product family made it extremely difficult to produce a forecast accuracy at the end product level more than 10% with the best forecasting techniques. However, the calculation of accuracy, using the adjustment shown in (5) of additional possible build with excess material from over-forecast end products resulted in a better forecast accuracy at the product and month levels at 24%, as given in Fig.(4).

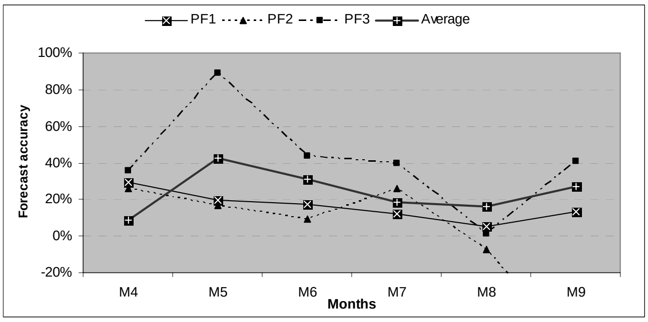

Figure 4 : Product level forecast accuracy for the top 3 families and the average

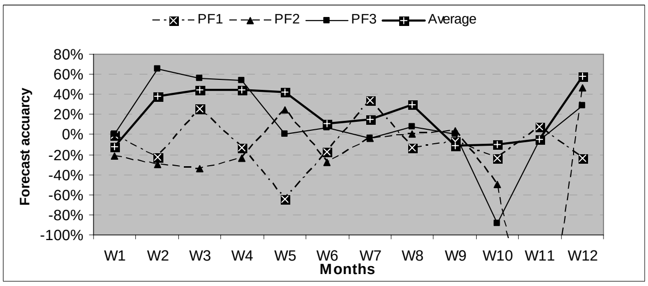

Figure 5 : Time level forecast accuracy

Table I : Product level accuracy

Prod Family	Demand	Product level accuracy
PF1	19%	16%
PF2	17%	1%
PF3	13%	42%
PF4	12%	11%
PF5	11%	50%
PF6	11%	22%
PF7	10%	54%
PF8	6%	25%
PF9	2%	-70%

With these results, the PBOM accuracy at the product level per equation 6 was calculated as 33%. Further to this, the time level forecast accuracy was calculated by splitting the monthly forecast into weekly level according to the accounting calendar of the organization, which had 4-4-5 weeks for every quarter. Here again, the Exponential smoothing was used for calculating the week level attach rates. The attach rates of weeks for every month always add up to 100% because both the actual value and the forecast value of the previous period according to the formula in (9) constrain the sum of attach rate to 100%. Smoothing constant value of 0.9 offered best results with time level forecast accuracy of 18%, as given in Fig.(5). This would translate into the time level PBOM accuracy of

75%.

Though the forecast accuracy at the end product and week level was low, the right first time assembly due to material shortage was marginally higher because of the following reasons

1. Assembly build is related more to the accuracy based on negative errors (under-forecast), worked out as 51% at the product level.
   However, the PBOM accuracy measurement would continue to be measured on the basis of absolute error, due to the broader perspective of inventory control requirements on positive errors.
2. The orders accepted from the priority customers without going through the systematic Available To Promise (ATP) checking process caused the MRP to generate expedite orders for suppliers.

D. PBOM reorganization

The PBOM profile was reviewed using the percentage demand and product level forecast accuracy as shown in table I and one of the product families, PF2 was identified as a potential candidate for reorganization.

The end products of the product family, PF2 were re-organized into 3 PBOMs and the aggregation noise was calculated as shown in table II and found satisfactory for further attach rates calculation.

Table II : Aggregation noise for re-organized PBOMs

Weights	Wa	Wb	Wc	Wd	Aggregation noise
	0.25	0.25	0.25	0.25	
Prod Family	Coeff of Variation	Unique Components %	No of end products	Important Customer %	
PF1	37.98%	3.00%	100	100.00%	64%
PF2A	10.00%	0.02%	15	0.00%	6%
PF2B	27.16%	0.03%	60	0.00%	22%
PF2C	41.00%	0.05%	82	0.00%	31%
PF3	39.95%	13.00%	30	0.00%	37%
PF4	41.44%	4.00%	47	100.00%	53%
PF5	26.51%	5.90%	17	100.00%	45%
PF6	37.22%	1.00%	61	0.00%	26%
PF7	43.73%	3.20%	31	0.00%	24%
PF8	22.21%	2.60%	39	0.00%	19%
PF9	97.77%	16.70%	6	0.00%	52%

This caused the product level PBOM accuracy increase to 51%, which meant that 50% of the right forecast could be realized with material availability in the line Right First Time. The product level attach rate accuracy and the time level accuracy were calculated as 38% and 28%, respectively with the new PBOM profile.

E. Business benefits

The metric for forecast accuracy, which would cause a direct improvement on right first time assembly was generated. The percentage of right forecast at family level, which could be realized with appropriate material availability for right first time was increased from 33% to 50%.

V. CONCLUSION

The demand management in ATO environment has a high dependency on the component level demand accuracy to improve the on-time delivery and control the inventory. This necessitates both the forecasting process and the demand translation process to be measured and reviewed. The proposed Planning Bill of Material (PBOM) process and model for the automotive components industry has helped to control the demand translation process by decomposing the problem into having accurate PBOM profiles and forecasting the product level attach rates and time level attach rates and measuring them with the suggested metrics on PBOM accuracy.

VI. FUTURE WORK

The demand translation challenges due to global sourcing scenario in the automotive components industry are multi-dimensional. They include the variation in component lead time, the variation in the customer preferred features and the short life cycle of the end products. There is a need to model this growing complexity of these factors. The authors are continuing their research towards an adaptive solution for these needs.

ACKNOWLEDGMENT

The authors wish to thank Mr. Prasad Satyavolu for his insightful comments and guidance on this research and Ms. Sunitha M Gopal for her support on identifying the opportunities for the conference.

ABBREVIATIONS

ATO – Assemble To Order
ATP – Available To Promise
MAPE – Mean Absolute Percentage Error
MPS – Master Production Schedule
MRP – Materials Requirements Planning
PBOM – Planning Bill Of Material
SIC – Statistical Inventory Control
VMI – Vendor Managed Inventory

REFERENCES

[1] J. W. M. Bertrand, M. Zuijderwijk and H. M. H. Hegge, “Using hierarchical pseudo bills of material for customer order acceptance and optimal material replenishment in assemble to order manufacturing of non-modular products” in *International Journal of Production Economics*, Volume 66, Issue 2, 30 June 2000, pp. 171-184.

[2] J.C. Wortmann, “Information systems for Assemble-To-Order production: An application” in *Engineering Costs and Production Economics*, Volume 12, 1987, pp. 187-196.

[3] Mihail S. Romanos, “Demand forecasting for parts used in modular products: A case study” in *Engineering Costs and Production Economics*, Volume 17, Issues 1-4, August 1989, pp. 231-244.

[4] Samir Lamouri and Andre Thomas, “The two level master production schedule and planning bills in a just in time MRP context” in *International Journal of Production Economics*, Volume 64, 2000, pp. 409-415.

[5] Baki Billah, Maxwell L. King, Ralph D. Snyder and Anne B. Koehler, “Exponential smoothing model selection for forecasting” in *International Journal of Forecasting*, Volume 22, Issue 2, April-June 2006, pp. 239-247.

[6] K. F. Lam, H. W. Mui and H. K. Yuen, “A note on minimizing absolute percentage error in combined forecasts” in *Computers & Operations Research*, Volume 28, Issue 11, September 2001, pp. 1141-1147.

[7] Kristie Huntress, “Evolution in the Demand and Supply planning at Dow Corning” in *The Journal of Business Forecasting*, Winter 2004-05, pp. 10-16.
[8] Alessandro Personaa, Daria Battinia, Riccardo Manzinib and Arrigo Pareschi, “Optimal safety stock levels of subassemblies and manufacturing components” in *International Journal of Production Economics*, 2007.
[9] Professor Hossein Arsham, “Time-Critical Decision Making for Business Administration” in *http://home.ubalt.edu/ntsbarsh/stat-data/Forecast.htm*.
[10] Petri Hautaniemi and Timo Pirttila, “The choice of replenishment policies in an MRP environment” in *International Journal of Production Economics*, Volume 59, Issues 1-3, March 1999, pp. 85-92.