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Augmenting Statistical Forecast In Oracle Demantra With Pre Analytics Of Sales Data

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Abstract

Effective S&OP / IBP is critical for organizational goals of delivering profit and customer satisfaction by striking balance between supply and demand. Getting reliable forecast is one crucial factor that decides the success of S&OP / IBP process in the organization. This makes demand planning one of the critical input for the S&OP/IBP process of the organization.
Demand planning function is collaborative efforts coordinating between several departments including sales, marketing, fiancé and operations. Forecasting need to ensure that forecast data is available at different levels that support the key stakeholders.
Oracle Demantra is a very powerful and flexible tool that provide the demand management capabilities. Demantra has strong integration with Oracle E-Business suite applications providing end to end support for supply chain planning activities. Oracle Demantra can also be used in standalone mode providing flexibility to integrate with other 3rd party applications.
Demantra demand management application has strong capabilities to generate forecast at detailed and / or aggregate level. It also provides capabilities to collaborate and post adjustments at different levels and aggregation levels of hierarchy.
This article is intended to assist organizations decide on designing Demantra demand management forecasting engine for effective forecasting. The articles provide details about basic building blocks of Demantra forecasting engine. Then it discusses the dependency between sales data aggregation and forecasting engine design. The example discussed in this article provides some insight into the benefits of data aggregation before loading to Demantra.

Keywords:

Oracle Demantra Demand Management;
Oracle Demantra Real Time;
Sales and Operations Planning
Oracle ASCP;
Integrated Business Planning (IBP);
Sales and Operations Planning (S&OP)

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1: Introduction to Demand Planning and Oracle Demantra

Demand planning is key building block for the supply chain planning.
The demand planning process starts with activity to collect historical data and generate statistical forecast. The forecast is then distributed to other stakeholders and received feedback. Key stakeholders that can contribute to the forecast review process are sales, marketing, projects team. These stakeholders can provide valuable information about promotions, new accounts, impact of change in business scenario in their respective sphere of influence.
Demand planners can review the exceptions if any related to feedback. The forecast review process then focuses on reviewing and resolving exceptions. The demand planners can accept, reject or override the forecast and finalize the forecast. This forecast is demand that organizations intends to fulfill within forecasting horizon.
Oracle Demantra product suite is very powerful application that can help organizations achiever effective demand planning. Oracle Demantra has most important module of Demantra Demand Management (DM)

which is widely implemented. Demantra Demand Management generates the statistical forecast. This forecast is the starting point for Supply Chain Planning process.
There are additional modules of Real Time Sales and Operations Planning, Trade Promotion, Predictive Trade Planning that are focused for specific functions.
This articles focuses on collecting and evaluating the history data to get maximum benefits of Oracle Demantra Demand management forecasting.

2: Basic components of Demantra
We can classify Oracle Demantra components into 2 parts - User Interface and Business Modeler.
Oracle Demantra uses worksheets for the user interface. Below is a sample screenshot of worksheet –

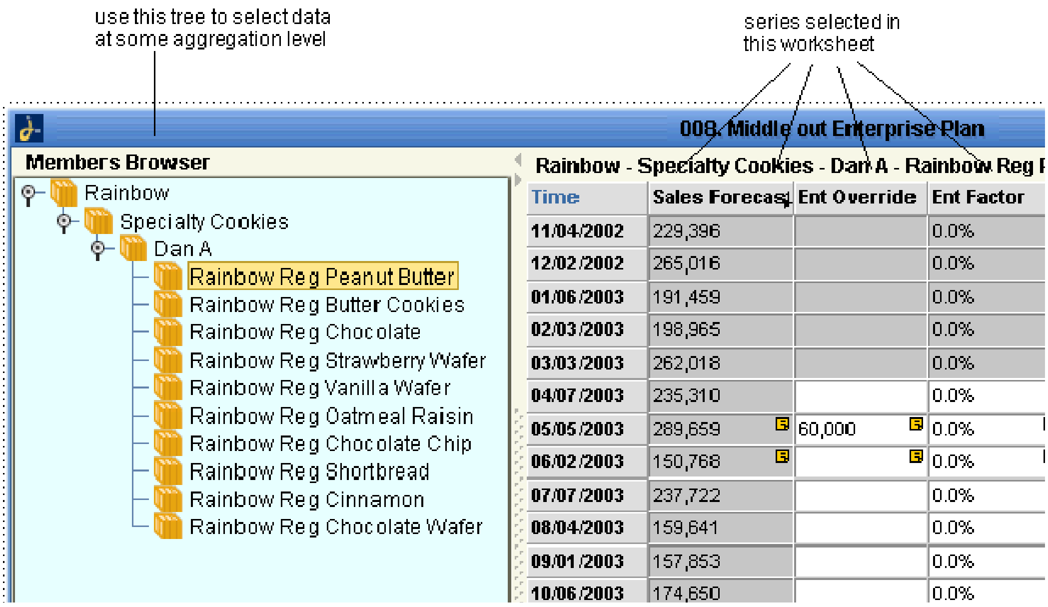

Figure 1. Sample screenshot of worksheet [1]

Users can view, filter and edit data in a worksheet and sabe changes to database. The data is organized by 'hierarchy' in the worksheet. Users can apply the filters on hierarchy to slice and dice the data. The time series data is displayed in the series. Each series represents stream of time dependent data. Users can modify and save data in the series that are editable. The series data can be aggregated at a higher level based on hierarchy selection. The data can be edited at aggregate level. However depending on the rules, the data will be allocated and stored at the lowest level of hierarchy.
Business modeler is a tool used to configure Demantra. Typically, expert consultants have access to Demantra Business modelers for the configuration tasks. Users can define, level, hierarchy, series, integrations in business modeler.
A sample screenshot of business modeler –

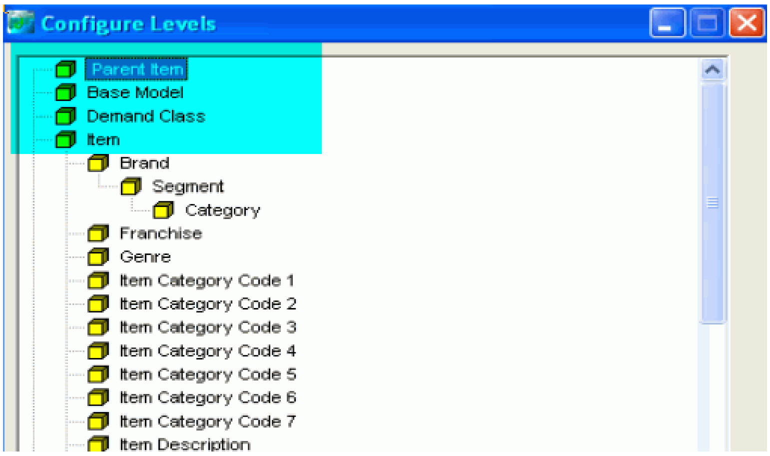

Figure 2. Sample screenshot of Demantra levels [1]

One of the most important part in business modeler is defining statistical forecast engine.

3: Introduction to Level and hierarchy of Demantra

Demantra stores, processes and displays data for 'combinations' of levels. In any basic Demantra implementation following key levels need to be defined -

Item Level --> This level captures the saleable entity for which forecast need to be generated.

Customer Level --> This level captures the customer details.

Site --> This level captures the site of customers where the sales or consumption took place.

Organization --> This level captures the organization that served the demand.

Example: data from a typical sales order record is mapped to Demantra levels and series as follows –

COMBINATION - Defined with Levels				Time and Time Series Data	
Item	Customer	Ship To Site	Organization	Schedule Ship Date	Quantity
AS54888	Computer Services	Chattanooga (OPS)	Seattle Distribution Center	1-Nov	100

Table 1. Data from a typical sales order record.

4: Introduction to Statistical Models and Forecast Tree

Forecast engine configuration is a vital activity of the Demantra implementation. The forecast engine configuration decides the statistical forecast output of Demantra which is foundation of all supply chain planning.

Demantra forecast engine has 2 important parts –

1: Selection of Statistical methods and setting up of parameters

Demantra basic configuration provide following statistical methods –

Holt
Auto Regressive External Inputs
Auto Regressive Integrated External
Causal Winters
Combined Transformation
Croston for Intermittent
Dual Group Multiplicative
Regression for Intermittent
Transformation Regression
Regression

Additional statistical models can be enabled with implementation of Advanced Forecasting and Demand Modeling (AFDM). AFDM offers additional key capabilities of shape modeling, base and lift decomposition, localized nodal tuning.

2: Setting up forecast tree.

Demantra calculation engine uses forecast tree to decide the aggregation level if there is no enough data to generate forecast at lower level. With the forecast tree configuration, user can instruct the engine the order in which data can be aggregated.Example screenshot of Forecast Tree in Demantra –

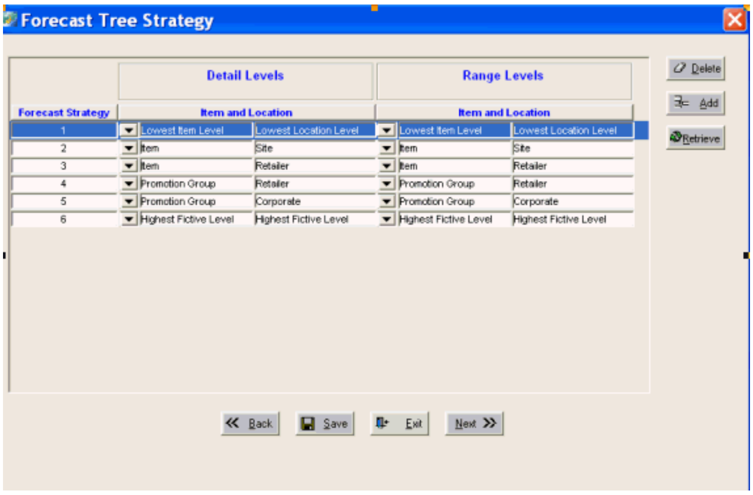

Figure 3. Sample screenshot of Demantra Forecast Tree [1]

For example, assume following item, customer and ship to location hierarchy are defined –

Item: Item is lowest level. The next aggregation level is Product Family. Multiple items can be grouped under one product family. Product Families are aggregated under ‘Market Segment’. This is represented as follows -
Item → Product Family → Market Segment

Customer: Customer is lowest level of customer hierarchy. Multiple customers are aggregated under ‘Customer Group’. Multiple customer groups are aggregated under ‘Customer Region. This is represented as follows:
Customer → Customer Group → Customer Region

Ship To Location: This is the actual customer location. Multiple ship to locations are aggregated under ‘Ship To Region’. Multiple ship to regions are aggregated under ‘Ship To Country’. This is represented as follows:
Ship To Location → Ship To Region → Ship To Country

Organization: This is the organization location, warehouse, or plant, from which the demand is fulfilled. Multiple organizations are aggregated under ‘Supply Zone’. Multiple supply zones are aggregated under ‘Supply Region’.
Organization → Supply Zone → Supply Region

Few possible forecast treeconfigurations are –

Forecast Strategy	Item and Location	
1	Lowest Item Level	Lowest Location Level
2	Product Family	Ship To Location
3	Product Family	Ship To Region
4	Product Family	Ship To Country
5	Highest Fictive Level	Highest Fictive Level

Table 2. An example of Forecast Tree with item level aggregation

In this case, the first aggregation takes place based on item hierarchy. If there is no enough data found for certain combination then engine will aggregate data at product family level for the particular ship to site and try to generate forecast.

Forecast Strategy	Item and Location	
1	Lowest Item Level	Lowest Location Level
2	Item	Ship To Location
3	Item	Ship To Region
4	Item	Ship To Country
5	Highest Fictive Level	Highest Fictive Level

Table 3. An example of Forecast Tree with Ship To Level aggregation

In this case, the first aggregation is by Ship To Site hierarchy. If there is no enough data found for certain combination then engine will aggregate data for that item across Ship To Region and try generate forecast.

An example with customer hierarchy is –

Forecast Strategy	Item and Location	
1	Lowest Item Level	Lowest Location Level
2	Item	Customer

Forecast Strategy	Item and Location	
3	Item	Customer Group
4	Item	Customer Region
5	Highest Fictive Level	Highest Fictive Level

Table 4. An example of Forecast Tree with Customer level aggregation

An example with organization hierarchy –

Forecast Strategy	Item and Location	
1	Lowest Item Level	Lowest Location Level
2	Item	Organization
3	Item	Supply Zone
4	Item	Supply Region
5	Highest Fictive Level	Highest Fictive Level

Table 5. An example of Forecast Tree with Organization level aggregation

5: Analysis of Demand History data and aggregation

Configuration of level data and forecast tree aggregation can significantly help on output of statistical engine. This article discusses an idea to conduct analysis of demand history and make decision about sending aggregated data to Demantra as lowest level of hierarchy.

The aggregation of sales data complements the forecast tree and helps forecast engine select better statistical engines.

Sales data has 4 basic levels – Item, Customer, Ship To Site and organization. The data can be loaded to Demantra for every item, every customer, every ship to site and every organization combination. Forecast tree can be configured for multiple forecast strategy.

The disadvantages of this approach are -

- A higher number of combinations may have intermittent forecast generated. This results in spikes and valleys in statistical forecast.
- A higher number of combinations will be considered as exceptions which may overwhelm demand planners. Demand planners may not be able to complete forecast review for every reported exception.
- Adjustments posted at aggregate level are calculated and stored at lower level. This adjustment rules may not be same for all the combinations. This may cause a discrepancy in the reporting of data.
- For the combinations where aggregation from forecast tree is used and allocated forecast back, there may be discrepancy in the history and forecast patterns. It is possible that the combination has intermittent demand history but relatively smoother forecast. It becomes hard for demand planners to explain.
- Whenever Demantra is unable to generate forecast at all levels for a combination then it uses naïve models. The forecast is similar to simple average method.

Aggregating data can offer several advantages –

- Often history data at aggregate level tends to be smooth eliminating spikes and dips.
- Smoother history pattern is better to detect seasonality, trend and cyclic patterns for the forecast.
- Sending data at aggregate level reduces the number of exceptions for Demand Planners. Forecast review process becomes effective since less numbers of exception scenarios need to be resolved.
- Forecasting at SKU level offers advantage for capacity planning and manufacturing standpoint. Since aggregate level forecast has better trend, seasonality and cyclic pattern detection, the forecast is more accurate. This helps capacity planning in long term decision impacting investments as well as short term decision on capacity allocations.

It is often found that aggregating data for customers and / or organizations offers significant advantages. In one such exercise by an organization, forecasting was taking place at Item – Customer – Ship To Site and Organization level. Data from each organization was sent to Demantra for forecasting. This forecast was published to Supply Planning at organization level. With this approach, following challenges were faced –

- When orders were received, sales orders were assigned to the closest warehouse. But often due to availability of inventory, customer service changes warehouses to larger warehouses where inventory was available. This started building history in unwanted warehouse. The Demand planners spend lot of time changing demand history from one warehouse to another warehouse.
- Forecast errors were measured at lowest combination level. Demand history at lowest combination level was intermittent. But forecast tree used to evaluate forecast at aggregate level and then allocate it back to lowest individual combination level. This often resulted in discrepancy in the demand history pattern and forecast pattern. Demand planners struggled to explain the forecast errors.
- In order to improve on forecast errors, demand planners preferred simple average methods and override statistical forecast entries with one single average to full forecast horizon. This started impacting long term capacity planning. Since there is no trend, seasonality in the simple forecast average, long term capacity planning decision were often difficult.

Analysis of sales history was done and found that instead of feeding organization data to Demantra for forecasting, data can be aggregated at 'Supply Region' level and generate forecast at that level. Then forecast was published to supply planning engine. Using the historical data, forecast allocation to actual organization from the supply region was calculated and then forecast was allocated to organization for supply planning purpose.

Advantages of this approach –

- Number of combinations reduced approx. 8%
- Demand planners do not need to do forecast adjustment and move forecast from one warehouse to another warehouse. This function is moved to organization allocation in supply planning. This enabled demand planners to have better discussion on forecast review with other stakeholders.
- Demantra detected more combination with smooth demand history for the supply region. This improved the forecast accuracy for the Item – Customer – Ship To Site level forecast.

As a next phase of evaluation of aggregation, Ship To Site and Customer data was picked up. In this phase apart from quantitative data, feedback from customer service was also important. From a customer service standpoint, there were few customers which were considered as 'Key Customers'. These customers were part of collaborative planning exercise. Customer service representatives often compare Demantra generated forecast with customer generated forecast and come up with consensus forecast with key customers. Hence it was mandatory to send data of those customers to Demantra and generate customer level forecast for the Key Customers. Based on the feedback of customer service about key customers and evaluating other customers for aggregation, sales data was loaded with dummy customer – OTHER CUSTOMERS for the region.

At the end of this exercise –

- Number of combinations reduced by 85%
- Demantra detected high number of combinations with smooth demand history
- The hybrid approach to exclude Key customers from data aggregation helped customer service still generate customer level forecast for key customers.
- The forecast at item level published for capacity planning has higher reliability due to better detection of trend, seasonality and cycles at aggregate level.
- The design for Forecast tree in Demantra is simplified significantly. Instead of having high number of forecast strategies, only few forecast strategies could be defined.
- This also helped consultants pick up few key statistical forecast based on Demand Planners feedback and tune the parameters of the statistical engines.

Conclusion

Oracle Demantra Demand Management is highly flexible and powerful tool of demand planning . The tool offers capabilities of generating statistical forecast and collaboration to project the future by effectively combining the quantitative and qualitative inputs.

Demantra organizes the data into levels and hierarchies. Level represents the type of data and hierarchy represents the aggregation of the data type. Hierarchies with multiple aggregation levels can be defines for viewing and editing the data at aggregate level.
The combination of statistical models and forecast tree of Demantra demand management enables organizations to model multiple business scenarios for forecasting. Forecast tree enables user to decide the preferred path of aggregation and forecast generation. Multiple statistical models and flexibility to setup parameter for every statistical model helps organization support different history patterns like smooth demand history, intermittent demand history, lumpy demand history etc.
The section of demand history analysis and aggregation addresses the key question of defining the level and hierarchy. The impact of conducting analysis of demand history and defining the lowest level data that will be loaded to each level is immense on forecast review process. Aggregating data before loading the Demantra demand management can simplify forecast tree, statistical model selection and parameters setting. However the decision to aggregation of data before loading needs quantitative and qualitative inputs.

References

1. Oracle® Demantra Implementation Guide. (n.d.). https://docs.oracle.com/cd/E18727_01/doc.121/e05136/