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Optimization or Prioritization - Product Mix Decisions in Sales and Operations Planning

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Abstract: ***Effective S&OP/IBP is critical for organizational goals of delivering profit and customer satisfaction by striking a balance between supply and demand. Multiple stakeholders are impacted by the success of the S&OP/IBP process. Master schedulers can define an effective master plan, customer service can provide reliable promised dates based on the master plan, and material planners can better align and utilize constrained materials to achieve the objectives of the S&OP/IBP process. One critical decision point in sales and operations planning is achieving the correct product mix. A correct product mix can significantly improve organizational goals, optimize resource and material capacity constraints, and enhance customer satisfaction through reliable order promising. This article discusses key drivers to optimize the product mix, the optimization process, tools for optimization, and key inputs for these tools and processes. The article provides insights into two different approaches and their impacts on product mix optimization.***

Keywords: Sales and Operations Planning (S&OP), Integrated Business Planning (IBP), Resource Constraints, Optimization, Python programming language

1. Introduction

Sales and Operations Planning (S&OP) serves as a crucial link between tactical and operational planning. It is a monthly process during which key stakeholders review various contributing factors such as inventory, costs, resource and material capacities, lead times, and demand forecasts. The team then evaluates their impact on the tactical goals, sometimes referred to as the annual plan, set by the organization, and identifies any potential deviations. Based on this review process, the outcome of S&OP includes short-term operational plans and any new guidance needed for the long term.

The primary focal points of S&OP are supply, demand, volume, and product mix [1]. The consequences of an imbalance between supply and demand are straightforward. Insufficient supply leads to poor customer service, sales losses, increased costs from overtime or premium capacity charges, and higher freight rates. Conversely, excess supply results in inflated inventories tying up capital, reduced profit margins due to price reductions aimed at moving excess goods to market.

The impact of volume and product mix is more intricate but equally critical for the success of the S&OP/IBP process. For instance, if supply volume is reviewed at an aggregate level (like by product family) and an operational plan is finalized without considering product mix, there's a risk that the exercise in balancing supply and demand won't yield desired outcomes. Similarly, neglecting product mix in S&OP/IBP discussions and leaving each function to decide independently can lead to conflicting objectives. For example, sales may prioritize highly profitable products within a product family to meet their sales targets, potentially increasing manufacturing lead times. Consequently, manufacturing might deprioritize these products in favor of shorter lead time items, affecting overall supply chain efficiency. This will result in a high backlog for one product and higher unused inventory on the other side.

For example, assume there are four products under a product family – Item – A, Item – B, Item – C and Item – D. Below table is example of product mix desired by sales team.

Table 1: Product mix desired by Sales team

	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6
Total volume - Product Family level	1000	1000	1000	1000	1000	1000
Item - A	550	550	550	550	550	550
Item - B	300	300	300	300	300	300
Item - C	100	100	100	100	100	100
Item - D	50	50	50	50	50	50

However, the product mix desired by manufacturing based on lead times, setup times, available capacities is different and is shown in table below.

Table 2: Product Mix desired by Manufacturing

	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6
Total volume at Product Family level	1000	1000	1000	1000	1000	1000
Item - A	50	50	50	50	50	50
Item - B	200	200	200	200	200	200
Item - C	250	250	250	250	250	250
Item - D	500	500	500	500	500	500

In this case, there will be backlog in ‘Item-A’ and excess inventory on ‘Item -D.’

Defining the product mix as part of Sales and Operations Planning (S&OP) establishes clear ownership of the volume in the operations plan. Some of the most significant benefits of defining the product mix as part of S&OP include:

- The product mix fosters clear communication between the manufacturing and sales teams. Manufacturing

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receives clear guidance on the goods to produce, while sales gains clarity on incoming supply.

- The operations plan aids manufacturing and procurement in better aligning work orders and purchase orders, reducing frequent changes, cancellations, or overtime. The product mix brings stability to manufacturing activities and minimizes fluctuations.
- With sales having a clearer and more reliable picture of product supply, order promising becomes more dependable, significantly enhancing customer service.

2. Optimization Approach

In the case study, two different options were evaluated. The first option involves determining the product mix through optimization using linear programming, specifically integer programming. Linear programming is a mathematical technique where real-world problems are formulated using mathematical equations. The objective is to maximize or minimize a linear function, known as the objective function, subject to various constraints represented mathematically as inequalities.

For this exercise, the goal is to allocate capacity to items based on item priority, subject to the following constraints:

- Minimum requirement quantity must be met. This could be due to contractual obligations with customers regarding inventory levels or existing firm work orders that require allocated capacity.
- Maximum requirement is limited to either forecasted demand or current sales orders, whichever is higher. This constraint prevents overproduction, particularly important for items with limited shelf life, as overproduction leads to sunk costs and impacts profitability.
- Respect batch quantity or multipliers of items. Economic batch quantities determined by production capabilities are used as multipliers. Additionally, items may have specific case or box quantities that optimize production volumes.
- Available capacity for allocation, defined in terms of production volume. Total production volume cannot exceed this capacity.

A critical aspect of this approach is the prioritization of items. Capacity is allocated first to items with higher priority, followed by those with lower priority. In the optimization problem, item priority is modeled using 'Rewards'. Assigning a higher reward indicates that fulfilling demand for that item yields greater returns compared to others.

Following tables show representative data used in the model–

Table 3: Availability Capacity

Date	Available Capacity
1-Jan-23	1000
1-Feb-23	1000
1-Mar-23	1000
1-Apr-23	1000
1-May-23	1000

Table 4: Minimum and Maximum requirements for items each month

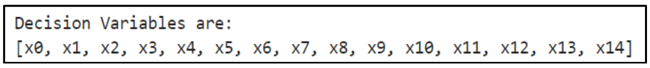
Item	Date	Minimum Requirement	Maximum Requirement
Item - A	1-Jan-23	0	500
Item - A	1-Feb-23	0	500
Item - A	1-Mar-23	200	500
Item - A	1-Apr-23	0	500
Item - A	1-May-23	0	500
Item - B	1-Jan-23	0	500
Item - B	1-Feb-23	200	500
Item - B	1-Mar-23	0	500
Item - B	1-Apr-23	0	500
Item - B	1-May-23	0	500
Item - C	1-Jan-23	0	500
Item - C	1-Feb-23	0	500
Item - C	1-Mar-23	0	500
Item - C	1-Apr-23	0	500
Item - C	1-May-23	0	500

Table 5: Multiplier and Penalty For items

Item	Multiplier	Reward
Item - A	30	5
Item - B	1	10
Item - C	1	15

The linear programming problem was represented as below –

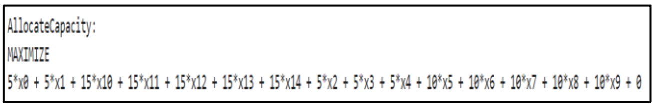
There is a decision variable defined for each time bucket, in this case month, for each item representing the quantity fulfilled for that item and month combination.



```
Decision Variables are:
[x0, x1, x2, x3, x4, x5, x6, x7, x8, x9, x10, x11, x12, x13, x14]
```

Figure 1: List of decision variables

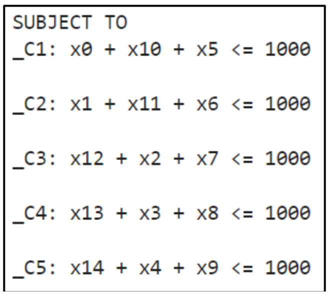
Objective function is defined to maximize the total reward. Total reward is fulfilled quantity for each item and time bucket multiplier by reward for each item.



```
AllocateCapacity:
MAXIMIZE
5*x0 + 5*x1 + 15*x10 + 15*x11 + 15*x12 + 15*x13 + 15*x14 + 5*x2 + 5*x3 + 5*x4 + 10*x5 + 10*x6 + 10*x7 + 10*x8 + 10*x9 + 0
```

Figure 2: Objective Function to Maximize the Total Reward

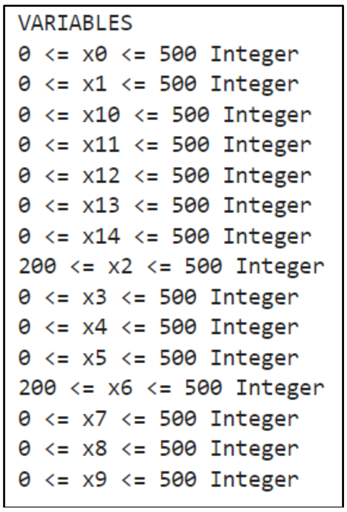
First constraint modeled is capacity constraint limiting the total fulfilled quantity is less than or equal to total available capacity –



```
SUBJECT TO
_C1: x0 + x10 + x5 <= 1000

_C2: x1 + x11 + x6 <= 1000

_C3: x12 + x2 + x7 <= 1000

_C4: x13 + x3 + x8 <= 1000

_C5: x14 + x4 + x9 <= 1000
```

Figure 3: Constraints of available capacity in each time bucket

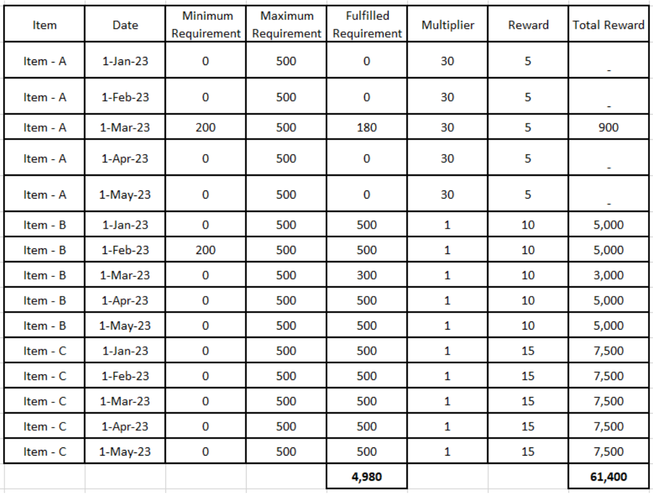
The fulfilled quantity needs to be greater than minimum requirement but less than maximum requirement. Additional constraint model here is that fulfilled quantity should be an integer -



```
VARIABLES
0 <= x0 <= 500 Integer
0 <= x1 <= 500 Integer
0 <= x10 <= 500 Integer
0 <= x11 <= 500 Integer
0 <= x12 <= 500 Integer
0 <= x13 <= 500 Integer
0 <= x14 <= 500 Integer
200 <= x2 <= 500 Integer
0 <= x3 <= 500 Integer
0 <= x4 <= 500 Integer
0 <= x5 <= 500 Integer
200 <= x6 <= 500 Integer
0 <= x7 <= 500 Integer
0 <= x8 <= 500 Integer
0 <= x9 <= 500 Integer
```

Figure 4: Minimum and Maximum requirement constraint with integer requirement

The solve results provide the highest possible capacity allocation in fulfilled quantity. The output from representative data is shown below –



Item	Date	Minimum Requirement	Maximum Requirement	Fulfilled Requirement	Multiplier	Reward	Total Reward
Item - A	1-Jan-23	0	500	0	30	5	-
Item - A	1-Feb-23	0	500	0	30	5	-
Item - A	1-Mar-23	200	500	180	30	5	900
Item - A	1-Apr-23	0	500	0	30	5	-
Item - A	1-May-23	0	500	0	30	5	-
Item - B	1-Jan-23	0	500	500	1	10	5,000
Item - B	1-Feb-23	200	500	500	1	10	5,000
Item - B	1-Mar-23	0	500	300	1	10	3,000
Item - B	1-Apr-23	0	500	500	1	10	5,000
Item - B	1-May-23	0	500	500	1	10	5,000
Item - C	1-Jan-23	0	500	500	1	15	7,500
Item - C	1-Feb-23	0	500	500	1	15	7,500
Item - C	1-Mar-23	0	500	500	1	15	7,500
Item - C	1-Apr-23	0	500	500	1	15	7,500
Item - C	1-May-23	0	500	500	1	15	7,500
				4,980			**61,400**

Figure 5: Output of the Capacity Optimization Problem

Several test cycles were conducted for different product family data sets. The number of items within a product family varied from 10 to 2000. The model was run by changing input parameters of Minimum and Maximum requirements, rewards for the same capacity constraint.

Key findings from these test cycles were as follows:

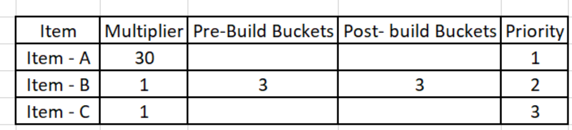
- Product families with a smaller number of items validated the model easily, confirming optimized outputs.
- Multiple runs with identical input parameters for smaller product families yielded similar results, with minimal or no recommended changes to the product mix.
- The model demonstrated sensitivity to 'Rewards'; items with comparable reward values were sometimes assigned capacity interchangeably. This effect was minimal in smaller product families but challenging to assess in larger ones.
- Determining rewards for product families with a high number of items proved challenging and time-consuming. In product families with numerous items sharing similar reward values, the model's output lacked consistency, often altering the product mix despite maintaining a similar total reward value.

3. Prioritization Approach

In this approach, capacity allocation was done strictly in priority order of the items. The input data points for available capacity, minimum requirement, maximum requirement and multiplier were same as that of optimization model. Instead of 'Reward', the items were assigned 'Priority' within the product family.

Additional parameters were defined for items –

- Pre-build buckets – This is the number of buckets earlier an item is allowed to produce before the actual demand. This is important in the case of items with expiration dates. The items should not be produced too early from the demand else it will result in high sunk cost
- Post-build buckets – This is the number of time buckets late an item is allowed to produce after the actual demand. This is important to avoid excess inventory due to loss of sales. Typically, this is tied back to customers willingness to accept goods with delay.



Item	Multiplier	Pre-Build Buckets	Post- build Buckets	Priority
Item - A	30			1
Item - B	1	3	3	2
Item - C	1			3

Figure 6: Item Attributes

In the above table, 'Item – B' is having limitation of pre-build and post-build buckets. This item can be produced 3 months earlier than actual demand or 3 months late than actual demand. Other items do not have any limitation. They can be produced in any time bucket within the horizon based on available capacity.

In this case, the capacity consumption starts with minimum requirement based on priority. In the above example, "Item – A' is highest priority item with priority 1 and has minimum requirement of 200 in the month of March 2023. Hence capacity in March 2023 will be consumed by 200 quantities first. Next capacity consumption will take place by 'Item – B' with priority 2 and minimum requirement of 200 in Feb-2023 month. Since 'Item – C does not have any minimum requirements there is not more capacity consumption.

Table 6: Available capacity after consumption by minimum requirement

Date	Available Capacity
1-Jan-23	1000
1-Feb-23	800
1-Mar-23	800
1-Apr-23	1000
1-May-23	1000

In the next step, incremental requirement is calculated for each item and time bucket. In the example above, for the 'Item – A', in the month of March 2023, maximum requirement is 500. Out of which 200 is the minimum

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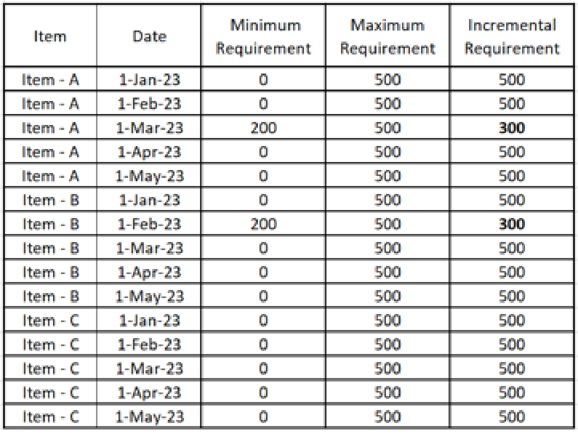
requirement, hence the remaining requirement to be fulfilled is 300.

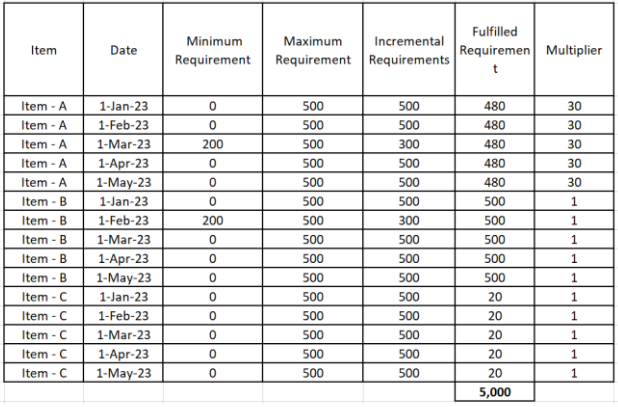
Table 7: Calculations for Incremental Requirements



Item	Date	Minimum Requirement	Maximum Requirement	Incremental Requirement
Item - A	1-Jan-23	0	500	500
Item - A	1-Feb-23	0	500	500
Item - A	1-Mar-23	200	500	**300**
Item - A	1-Apr-23	0	500	500
Item - A	1-May-23	0	500	500
Item - B	1-Jan-23	0	500	500
Item - B	1-Feb-23	200	500	**300**
Item - B	1-Mar-23	0	500	500
Item - B	1-Apr-23	0	500	500
Item - B	1-May-23	0	500	500
Item - C	1-Jan-23	0	500	500
Item - C	1-Feb-23	0	500	500
Item - C	1-Mar-23	0	500	500
Item - C	1-Apr-23	0	500	500
Item - C	1-May-23	0	500	500

Once the incremental requirement is calculated, then the cycle of capacity consumption repeats in the order of priority for incremental requirement. After the allocation of the capacity, multipliers are applied and fulfilled quantity is rounded down not to violate maximum requirement. This releases some capacity to lower priority items. For example, ‘ Item – A’ has multiplier of 30 and maximum requirement of 500. Full capacity is available for this item since this is priority 1 item. But due to the multiplier of 30, the fulfilled quantity is rounded to closed multiple of 30 which is 480.
After the complete cycle, the output of fulfilled quantity is –

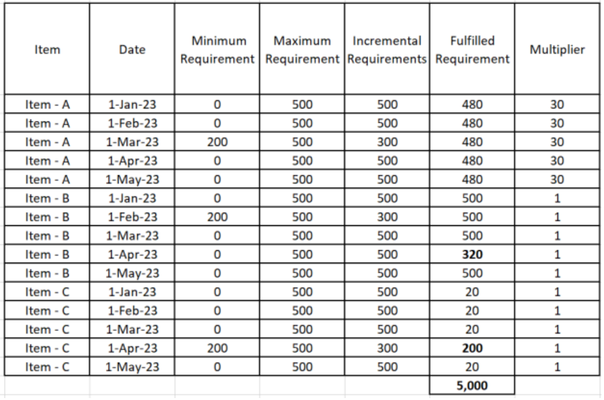
Table 8: Output of deterministic approach



Item	Date	Minimum Requirement	Maximum Requirement	Incremental Requirements	Fulfilled Requirement	Multiplier
Item - A	1-Jan-23	0	500	500	480	30
Item - A	1-Feb-23	0	500	500	480	30
Item - A	1-Mar-23	200	500	300	480	30
Item - A	1-Apr-23	0	500	500	480	30
Item - A	1-May-23	0	500	500	480	30
Item - B	1-Jan-23	0	500	500	500	1
Item - B	1-Feb-23	200	500	300	500	1
Item - B	1-Mar-23	0	500	500	500	1
Item - B	1-Apr-23	0	500	500	500	1
Item - B	1-May-23	0	500	500	500	1
Item - C	1-Jan-23	0	500	500	20	1
Item - C	1-Feb-23	0	500	500	20	1
Item - C	1-Mar-23	0	500	500	20	1
Item - C	1-Apr-23	0	500	500	20	1
Item - C	1-May-23	0	500	500	20	1
					5,000	

Below is output of another run with minimum requirement of 200 set of ‘Item – C’ in the month of Apr-2023.

Table 9: Output of Minimum Requirement consumption



Item	Date	Minimum Requirement	Maximum Requirement	Incremental Requirements	Fulfilled Requirement	Multiplier
Item - A	1-Jan-23	0	500	500	480	30
Item - A	1-Feb-23	0	500	500	480	30
Item - A	1-Mar-23	200	500	300	480	30
Item - A	1-Apr-23	0	500	500	480	30
Item - A	1-May-23	0	500	500	480	30
Item - B	1-Jan-23	0	500	500	500	1
Item - B	1-Feb-23	200	500	300	500	1
Item - B	1-Mar-23	0	500	500	500	1
Item - B	1-Apr-23	0	500	500	**320**	1
Item - B	1-May-23	0	500	500	500	1
Item - C	1-Jan-23	0	500	500	20	1
Item - C	1-Feb-23	0	500	500	20	1
Item - C	1-Mar-23	0	500	500	20	1
Item - C	1-Apr-23	200	500	300	**200**	1
Item - C	1-May-23	0	500	500	20	1
					5,000	

After this run, fulfilled requirement to ‘Item – C’ increases for the month of April 2023 and fulfilled requirement for ‘Item – B’ reduced for the month of April 2023.

Several test cycles were conducted for the same product family data sets as that of optimization.

Key findings from these test cycles include:

- Unlike optimization, the output of the program is deterministic for the set parameters. The number of test cycles does not alter the resulting product mix.
- The approach consistently performed well for product families with both a smaller number of items and a high number of items. Capacity consumption was consistently controlled by priority, resulting in predictable outcomes.

4. Conclusions

Effective sales and operations planning (S&OP) can deliver several benefits, including improved customer service, reduced backlog, efficient resource utilization, and ultimately, reduced costs leading to improved organizational profitability. As part of S&OP, defining the overall production volume at an aggregate level, such as by product family, is insufficient to fully realize these benefits. It is crucial to define the product mix within this volume to achieve a balanced alignment between supply and demand. Establishing a time fence for detailed review of the product mix and capacity allocation to each SKU is highly recommended.

Two different approaches were explored to define the product mix: Optimization and Prioritization.

Optimization: This approach offers benefits when the team can clearly define the objective function, such as cost reduction or profit maximization. However, it was found to be sensitive to the concept of 'Reward'. Determining the reward for each SKU proved challenging, and the optimization process often yielded varying product mixes in each run, creating uncertainty in the output.

Prioritization: In contrast, the prioritization approach consistently produced deterministic outputs without the variability seen in optimization. Assigning priorities to each SKU within a product family posed challenges similar to determining rewards in optimization. The overall cost or profit values from prioritization differed from those obtained through optimization using the same basic data set of capacity and requirements. Multiple iterations of prioritization were sometimes necessary to achieve desired outcomes.

Overall, the study revealed that optimization performs well with a smaller number of items at the aggregate level, providing stable product mixes. However, as the number of items increases, optimization may yield varying results with each run, introducing unpredictability. Prioritization, on the other hand, is more robust when dealing with a higher number of items at the aggregate level, though it does not guarantee optimal results for all objectives. Further research could explore combining both approaches to develop a hybrid method that leverages the strengths of each, potentially offering a more balanced and effective approach to defining the product mix in S&OP processes.

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Author Profile

Yashodhan Shashikant Shirolkar received a bachelor’s in mechanical engineering from Shivaji University in 2000 and Post Graduate Diploma In Industrial Engineering (PGDIE) from the National Institute of Industrial Engineering (NITIE, now Indian Institute of Management - IIM), Mumbai in 2002.He worked with manufacturing, consulting, and IT application development organizations for more than 20 years. His area of expertise is in Supply Chain Planning (Demand Planning, Supply Planning, Sales and Operations Planning, Inventory Management.). He has mainly worked with development, implementation, and supporting Oracle Applications. He has also done implementation, and support of non-Oracle applications. He has also developed and delivered several Python-based applications to support Supply Chain Planning functions in organizations. He is currently working with „ICU Medical Inc‟ as „Senior Manager for Planning Applications