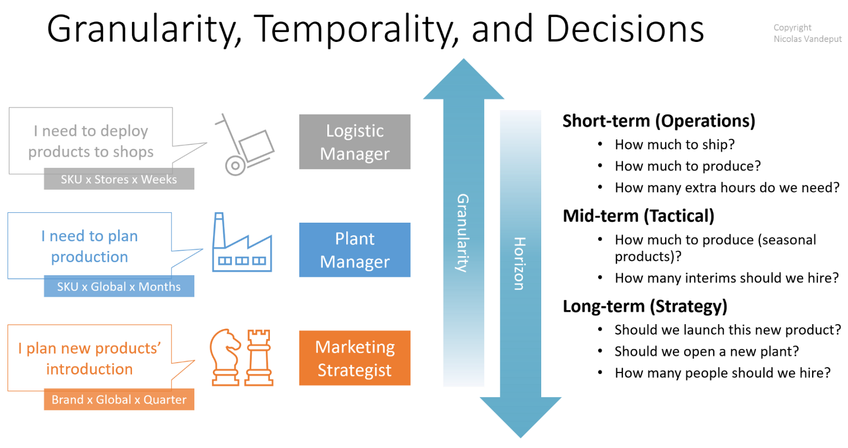
Should we Reconcile Forecasts to Align Supply Chain?

Supply chain management is about making decisions. Should we align teams using a 'one number forecast' or use a 'one number mindset'?

Demand Forecasting

Various teams and processes use a supply chain's demand forecast. As discussed in (Vandeput, 2021) and (Clarke, 2019), different stakeholders will have other requirements regarding the forecast material and temporal granularity. A logistic manager might be using the forecast to decide in which shops to ship goods in the next few days. A plant manager must plan her production for the next few weeks. A strategist marketer will use the same forecast to assess what new product to launch in the next six to nine months. A finance manager will communicate to investors based on a revenue forecast of the following quarters.



Supply chain management is about making decisions. How can we make sure that all these teams are aligned when making their forecasts (and the resulting decisions/plans)?

One Number Forecast?

In order to align all these stakeholders, many practitioners—as discussed in (Clarke, 2019) and (Bowman, 2013)—advocate for a **One Number Forecast** (i.e., a unified forecast shared by everyone across a supply chain); hoping that sharing a single unified forecast will *force* alignment across stakeholders. Thanks to current forecasting software, mechanically aligning forecasts across different temporal and material granularities is easy.

Still, it will come with challenges.

- **Efficiency.** First, you will face a tedious recurrent alignment process: can you imagine aligning every month the weekly forecasts of thousands of SKUs over the next 18 months?
- **Optimality.** Second, the optimal forecast (or model) at one material/temporal granularity level will not be optimal at another granularity (we will discuss this effect in the next section). One size can't fit all.
- **Alignment.** Finally, as explained by (Bowman, 2013), having a "one number forecast" won't guarantee that all the teams within a supply are aligned. (Bowman, 2013) discusses an example where Nestle USA agrees on a single number forecast during their S&OP process. And yet, each department was still performing some internal cooking.
  Let's take another simple example. You could agree in an S&OP meeting that the demand forecast is 100. Yet, the supply manager will produce 120 units, the sales manager will assume a sales target of 90, and the finance manager a revenue of 105. One unified forecast, and yet many different plans.

Different Granularities… Different Optimal Forecasts

A major issue of using a unified forecast is that a single forecast (or model) can't be optimal for all material and temporal aggregation levels.

Planners are often surprised to see that a forecast made at SKU level will differ from a prediction made at family level. This is normal and frustrating. Forecasters know well that **the forecast of the sum is not the sum of the forecasts**.

Beyond the math, let's discuss two business drivers behind this effect:

Spot Sales & Stock Clearances

The sales of a product family can be reasonably stable over time at an aggregated level. Whereas, at SKU level, you will see many spot sales due to flash promotions, surplus stock clearance, specific one-time sales, or contracts. Those spot deals are impossible to forecast precisely by SKU: forecasting models use historical demand to predict future sales. How could they predict stock clearances done on SKUs that have not been sold for a long time?

Top-down forecasts[1] can include some spot sales but won't be able to allocate them to specific SKUs. For example, if you know that you will do some stock clearance for a product family, you do not know precisely *which* SKU will be bought by your clients.

Moreover, demand planners should pay close attention *not* to include historical stock clearances to populate future forecasts. If not, they face the risk of triggering new replenishments for dying items.

Product life-cycles

(New) products come and go over time. As forecast engines use historical demand to predict future sales, you cannot expect a forecast engine to anticipate new SKUs' future introduction. On the other end, a forecast engine will spot any downward trend of a product nearing its end-of-life. This double effect will often bias a long-term bottom-up forecast. On the other hand, a top-down forecast–if the family portfolio is stable–will not suffer from this effect.

In conclusion, even if you can easily come up with a 18-months forecast at family level, translating it to a SKU level will not be optimal: you do not know which SKUs will compose this family's total sales (even if you can predict the main products).

[1] Top-down forecast: a forecast done at family level that is spread to SKU based on historical values.

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Example

As a demand planner, you are responsible for forecasting fruits. Fruits consist mostly of apples and bananas, plus a hundred other less-known fruits (that you usually do not sell). You know that you sell every month around 10.000 fruits (mostly apples and bananas, plus a few other less-known fruits).

If you forecast fruits sales at SKU level, your statistical engine forecasts a monthly demand of 9.500 fruits (apples and bananas). If you predict your fruit sales at an aggregated level, the engine shows an expected demand of 10.000 units. If measured at a total fruit level, this second aggregated forecast will likely be the most accurate. And yet, at SKU level, scaling the 9.500 apples and bananas forecast to 10.000 units (as shown in Table 1), might not result in any improvement–it could even remove value!

	Forecast	Scaled	Demand
Apples	4.500	4.737	4.500
Bananas	5.000	5.263	5.000
...	...	...	...
Kiwis	-	-	500
Total	9.500	10.000	10.000

Table 1 SKU Forecast vs. scaled forecast.

The difference between the SKU forecast (9500 units) and the family forecast (10000 units) is due to the unexpected sales of fruits that are usually not sold.

Conclusion

Scaling up the forecast of apples and bananas to 10.000 units will **destroy value** at the SKU level. Actually, at SKU level, you have no way to know which "less-known" fruit will be sold next month.

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Reconciling Probabilistic Forecasts

In many situations, working with probabilistic forecasts won't solve this reconciliation problem. It will make it worse. The demand for different items is *not* independent. (Some demand drivers will push all demand upward or downward, some clients might choose to buy either one product or another, etc.) So that the probabilistic distribution at a higher level of aggregation will not be the sum of the lower-level demand distributions (see an example in Table 2).

Forecast quantities	Apples	Bananas	Apples & Bananas
25%	2,000	2,000	5,000
50%	4,000	5,000	9,000
75%	7,000	9,500	15,000
95%	10,000	12,500	20,000

Table 2 Example of probabilistic forecasts reconciliation

On the other hand, a point forecast—as it is forecasting the average demand—is reconcilable at any aggregation level without issue: the total excepted demand at a granular level should be the same as the average expected demand at a global level.

This effect is well-known to forecasters: the M5 international forecasting competition asked for a different demand distribution for each aggregation level, but only one point-forecast at the most granular level.[1]

[1] See (MOFC, 2020).

One Number Mindset!

Next to the concept of *one number forecast*, a new idea emerged: **One Number Mindset**. Instead of forcing everyone to align on a single *number*, this construct proposes to align all stakeholders (planners, finance, marketing) on a single *mindset*. As advised by (Bowman, 2013) and (Wilson, 2019), the idea is to share assumptions, data, and a clear vision of the future rather than force everyone to align on every SKU's forecast (and fit all the requirements and teams in a single forecast process). Each team should be aware of any information that could impact demand such as pricing, marketing events, product introductions, competitors' actions, etc.

In practice:

- Every team should be required to use the same reconciled demand, pricing, and master data (as well as any other relevant information sources). A supply chain cannot allow two teams to use different historical figures to populate forecasts.
- A formal process should be set up to share information about events impacting demand (such as price change, marketing events, product introductions, competitors' actions…). The S&OP process can be the channel for information sharing across teams.

- Finally, forecasts done by various teams should be easily accessible by the other teams. To prevent any significant deviations from each other, all forecasts could be required to fluctuate within a specific (narrow) range. As discussed, small discrepancies are acceptable and natural, but any major discrepancy (anything higher than 5% at global level) will result in a lack of alignment between stakeholders.

With this aligned mindset and shared data, each function will be aligned despite working with a different forecasting process (with varying aggregation levels) and slightly different numbers.

Aligning teams thanks to a single mindset will allow every stakeholder to work on its required forecast granularity while enabling alignment on the main demand drivers (new product introduction, price changes, special events, and so on). This will leave more room for each team to define its own forecasting process using the most appropriate forecasting model, ultimately improving the overall forecasting quality. As explained by (Clarke, 2019), rather than influencing each other to achieve a single number forecast, teams will now have more time to discuss planning as they avoid reconciliation overload.

For example, a supply chain could have a S&OP process based on a country x month granularity. Nevertheless, to optimize the weekly deliveries from the global production plant to the local warehouses, another forecast could be made at a warehouse x weeks granularity. Both forecasts would be generated using the same historical demand dataset but using different models and review processes. Moreover, the short-term forecast will be reviewed by demand planners to make sure it sticks within a reasonable range compared to the S&OP forecast. If not, planners can easily scale the short-term forecast based on the S&OP numbers. Finally, any major event discussed in the main S&OP meeting (such as price changes or special sales) should be used to fine-tune the short-term forecast.

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Acknowledgment

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About the Author

Nicolas Vandeput is a supply chain data scientist specialized in demand forecasting and inventory optimization. He founded his consultancy company SupChains in 2016 and co-founded SKU Science—a fast, simple, and affordable demand forecasting platform—in 2018. Passionate about education, Nicolas is both an avid learner and enjoys teaching at universities: he has taught forecasting and inventory optimization to master students since 2014 in Brussels, Belgium. Since 2020 he is also teaching both subjects at CentraleSupelec, Paris, France. He published *Data Science for Supply Chain Forecasting* in 2018 (2nd edition in 2021) and *Inventory Optimization: Models and Simulations* in 2020.


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