Production Optimization for Short Shelf-Life Products

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Our story so far…

- For the last 18 months we have been working with a UK dairy manufacturer on a 2 year forecasting, production planning, and supplier replenishment project
- We have mapped 27 products, and won approval to improve their business processes
- We have tested our recommendations to forecast and plan the production and replenishment for a group of 9 products (i.e. we are actually creating the forecasts and schedules)
    - The nine products share a common base ingredient are in a range that goes to one customer and all share the same production equipment and labour
- We have implemented our forecast and production planning approach to an entire factory (producing 55 products)

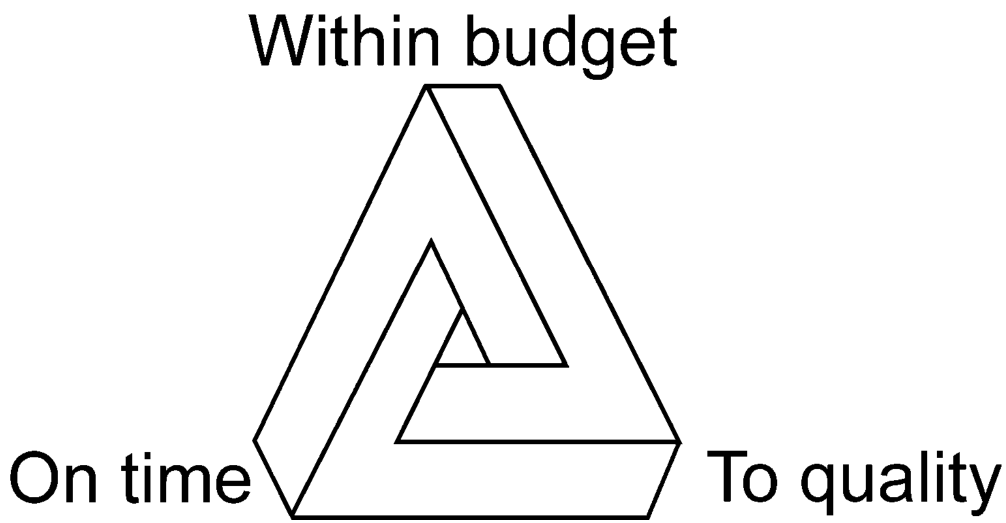
Sept 2017. Project start

Nov 2017. Mapped 27 different products

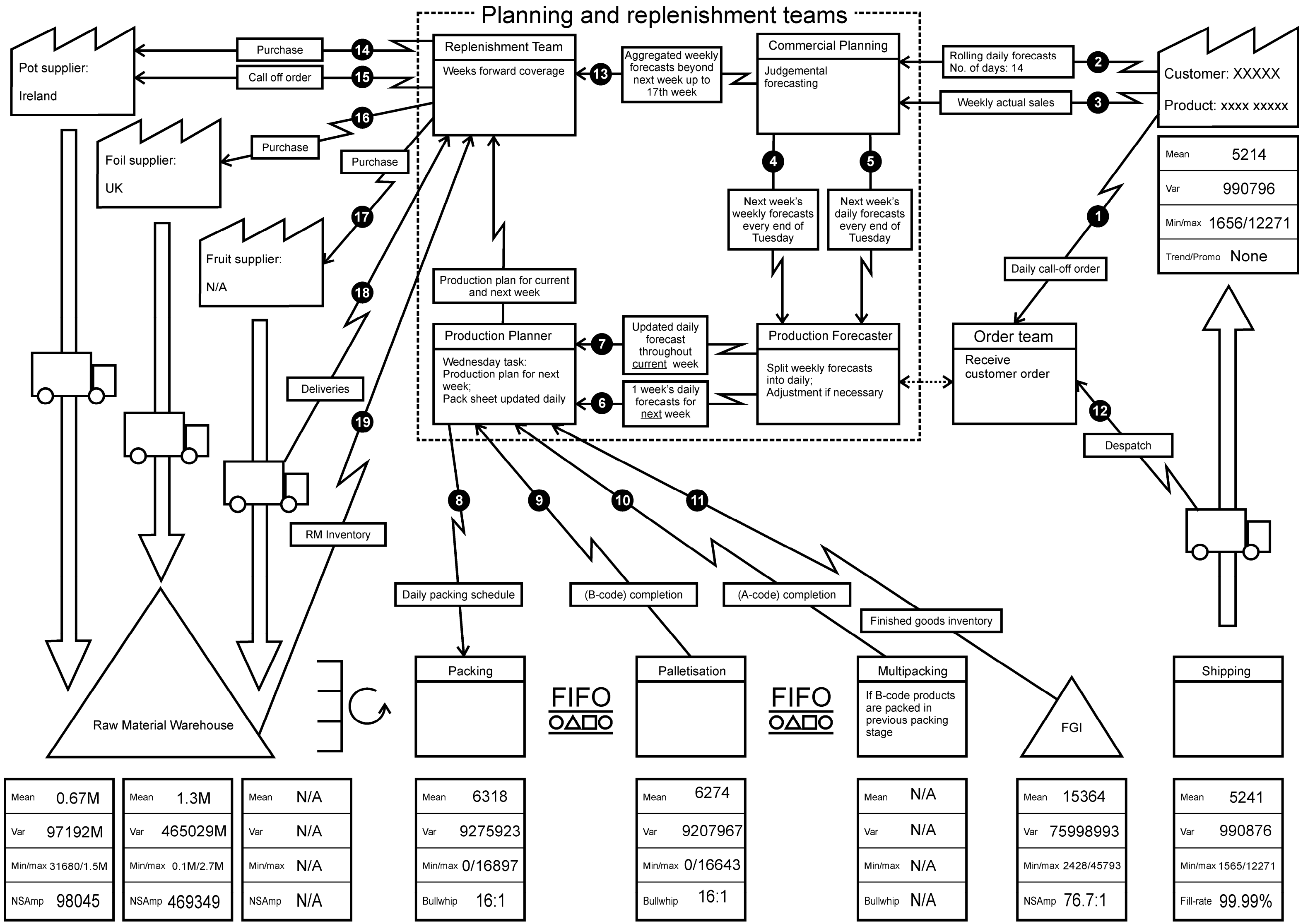
April 2018. Pilot study on a single product range of 9 products

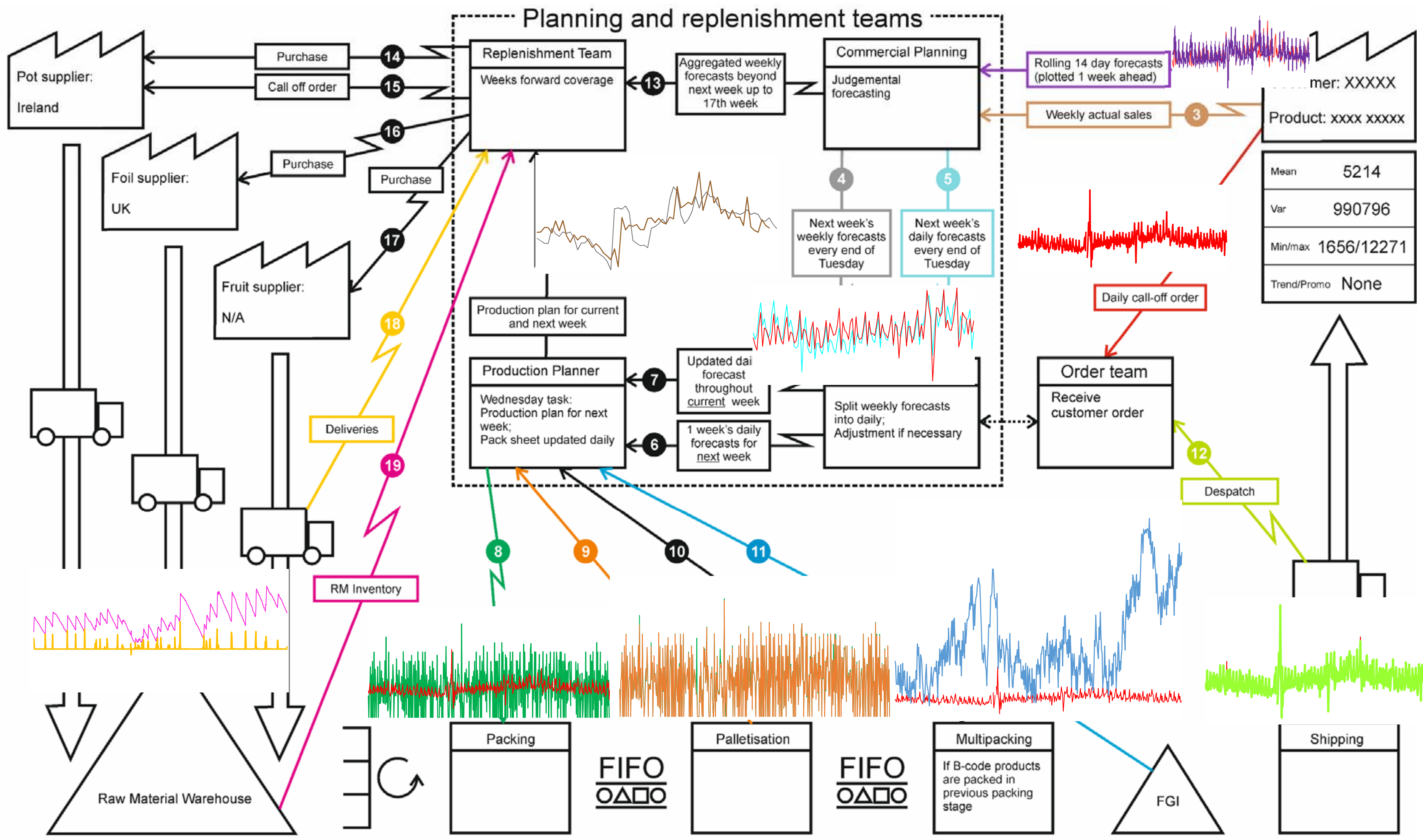
Oct 2018. Complete control of a factory producing 55 products

A dairy problem



Value Stream Mapping: Example from the 27 products





Planning and replenishment teams
Replenishment Team
Weeks forward coverage
Aggregated weekly forecasts beyond next week up to 17th week
Commercial Planning
Judgemental forecasting
Rolling 14 day forecasts (plotted 1 week ahead)
Weekly actual sales
mer: XXXXX
Product: xxxx xxxxx
Mean 5214
Var 990796
Min/max 1656/12271
Trend/Promo None
Pot supplier:
Ireland
Purchase
Call off order
Foil supplier:
UK
Purchase
Purchase
Fruit supplier:
N/A
Next week's weekly forecasts every end of Tuesday
Next week's daily forecasts every end of Tuesday
Production plan for current and next week
Production Planner
Wednesday task:
Production plan for next week;
Pack sheet updated daily
Updated dai forecast throughout current week
1 week's daily forecasts for next week
Split weekly forecasts into daily;
Adjustment if necessary
Daily call-off order
Order team
Receive customer order
Despatch
Deliveries
RM Inventory
Raw Material Warehouse
Packing
FIFO
Palletisation
FIFO
Multipacking
If B-code products are packed in previous packing stage
FGI
Shipping

Performance of SES forecasts

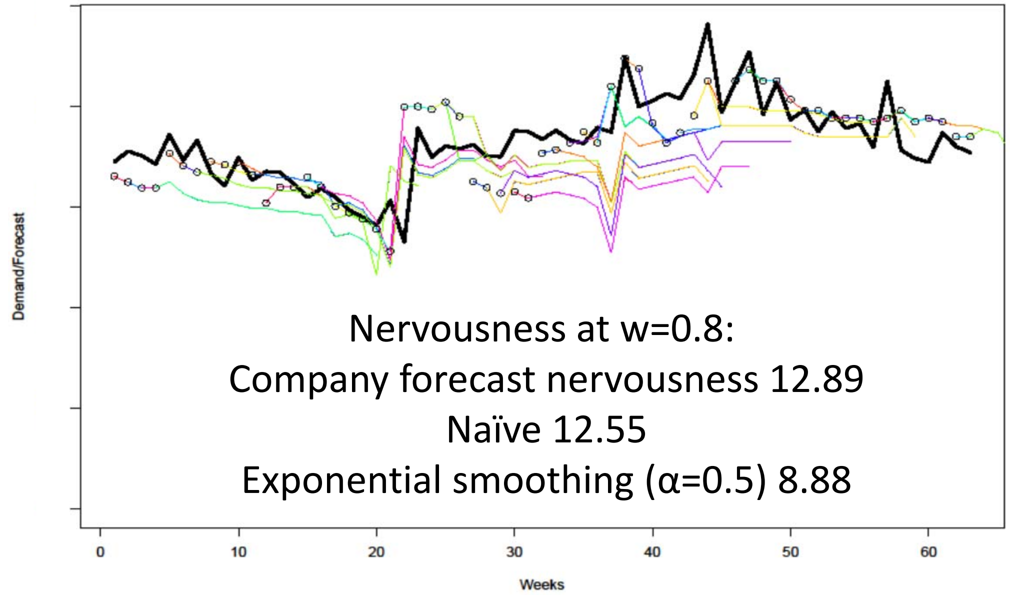
- We ran a forecasting competition to minimise the one-week ahead forecasting error (MSE).

Product	Exponential smoothing	Company	Customer	Best performer
Vanilla	12225	19300	35520	Exponential smoothing
Hazelnut	53319	68120	64489	Exponential smoothing
Raspberry	52583	78869	63907	Exponential smoothing
Lemon	120160	207338	140767	Exponential smoothing
Rhubarb	17660	45722	18389	Exponential smoothing
Strawberry	239079	271951	212784	Customer
Toffee	651575	712153	570016	Customer
Black Cherry	82991	134126	64041	Customer
Mango	3712	6733	12132	Exponential smoothing

- Exponential smoothing and manual over-ride at Christmas does the best

Forecast nervousness

- Li and Disney (2017) developed a measure of MRP nervousness.
- This can be used to measure the accuracy of future forecasts used to order long lead-time raw materials (pots and foils) and for financial planning



- The variance of the j-step ahead order forecast error is

$$\Delta[j] = \text{var}\left(d_t - \hat{d}_{t-j|t}\right)$$

The demand in period t

The forecast made at time t-j, of the order in time period t

- As a forecast error in the near future is more costly (or at least harder to deal with) than one in the distant future, we adopt a geometrically weighted sum of order forecast error variances as a measure of nervousness,

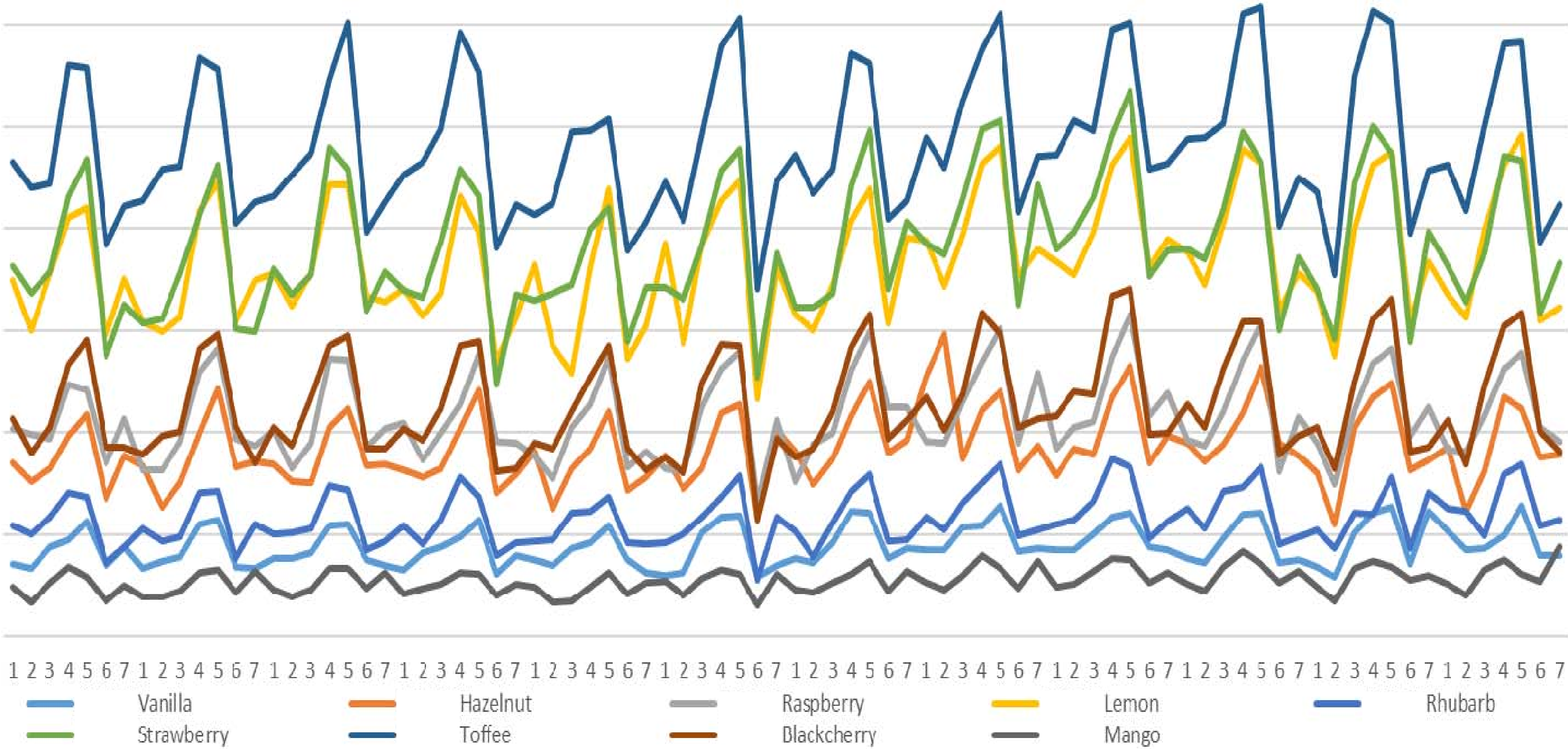
$$Nervousness = \Delta = \sum_{j=1}^{\infty} w(1-w)^{j-1}\Delta[j]$$

Li, Q., and Disney, S.M., (2017), "Revisiting rescheduling: MRP nervousness and the bullwhip effect", **International Journal of Production Research**, 55 (7), 1992–2012.

The 9 product pilot implementation

- We were given the Xxxxx Xxxxxx range to trail our recommendations
- We are scheduling the production of each of the nine products (each product is being produced twice a week)
- The company will use
  - Exponential smoothing forecasts, no manual interventions
  - A daily split based the last 3 months of demand, updated quarterly
  - A days forward coverage linked to the duration to the next scheduled pack
  - A constant safety stock target
- Once forecasts and production plans are made, no amendment is allowed unless there is machine breakdown, quality control issue, or raw material supply issue
- We expected
  - No shortage, no low code, and younger product to be sold to the customer, with the same financial performance.

A typical demand pattern



Forecasting the (7 day seasonal) daily demand

- If we aggregate the forecasts into weekly buckets there is little seasonality and exponential smoothing does really well.
- Nervousness was reduced by 30%.
- Forecasting team should be concerned with process supervision, not with chasing noise.
- Forecast done once a week on a Tuesday rather than being drafted on Tuesdays, updated on Wednesday and finalised on Thursday, with emergency revisions on Friday…
- The weekly forecasts are then split into daily forecasts. Company was using a rolling 4 week average to determine the daily split. This was introducing a lot of variation into the daily forecasts (snow days)
- **Recommendation.** The daily spilt should be based on a 3 month history of daily demands, updated every 3 months.

Production planning: Days forward coverage (DFC) methodology, 1 of 2.

- On Tuesday the daily demand is aggregated into weekly demand, a week is Sunday to Sunday

$$D_t = \begin{cases} \sum_{i=1}^{7} d_{t-2-i} & on\ Tuesdays \\ \varnothing & otherwise \end{cases}$$

- The weekly split, S_w

Day	Sun	Mon	Tue	Wed	Thur	Fri	Sat
Weekday, w	1	2	3	4	5	6	7
Proportion of weekly sales,	0.12	0.12	0.15	0.17	0.18	0.12	0.14

Production planning: Days forward coverage (DFC) methodology, 2 of 2.

- The weekly forecasts are split up into daily forecasts

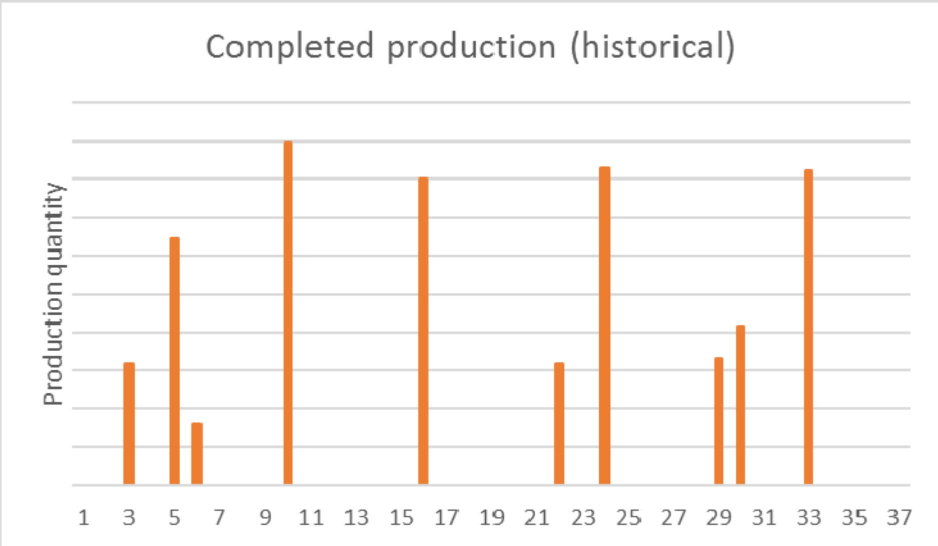
$$\hat{d}_{t+w-1} = \underbrace{s_w}_{\text{Daily split}} \underbrace{\hat{D}_{t-4-w}}_{\text{Last weekly forecast}}$$

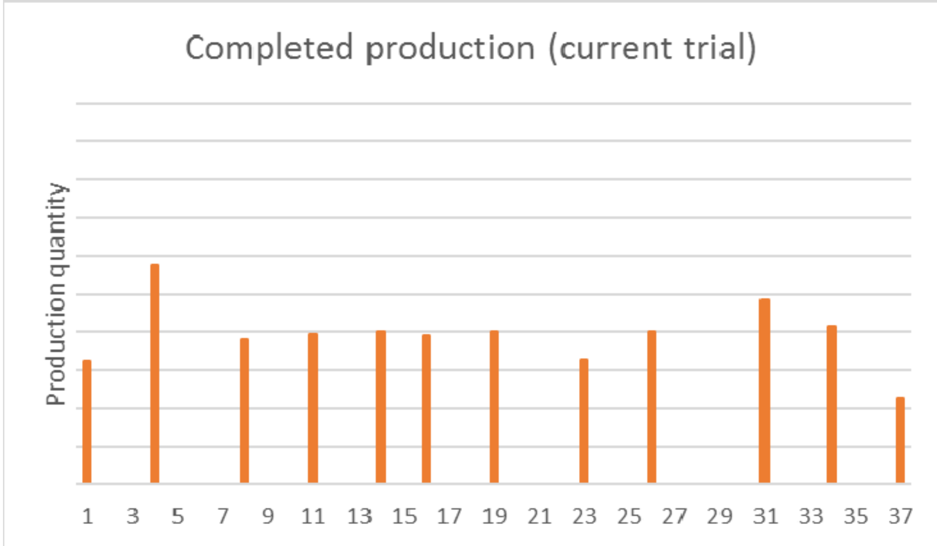
- Let f be the number of days until the next pack, then the production quantity is

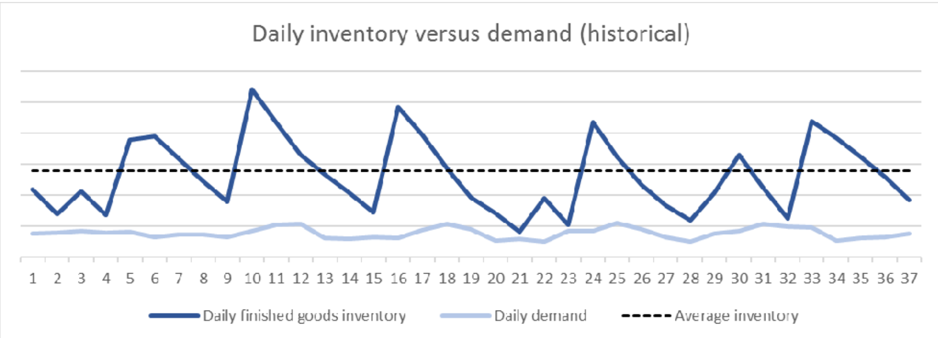
$$p_t = \begin{cases} \sum_{i=1}^{f} \hat{d}_{t+i|t} + \left(TNS - i_t\right) & \textit{if this product is due to be produced} \\ \varnothing & \textit{otherwise.} \end{cases}$$

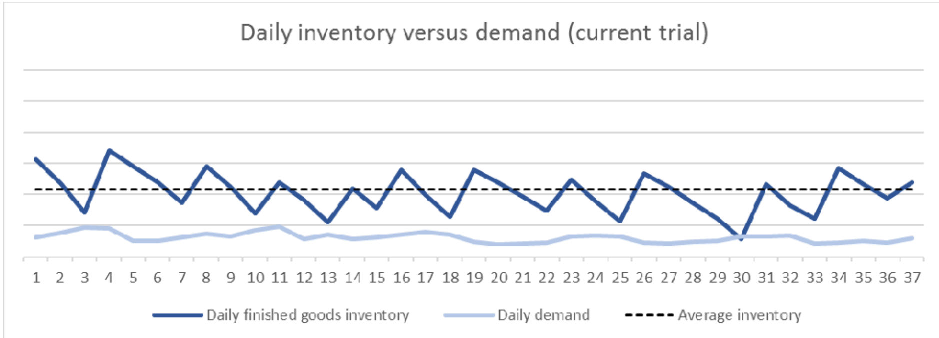
- Where $i_t = i_{t-1} + p_t - dispatch_t - lowcode_{t-1}$ is the inventory balance equation

Production and Finished Goods Inventory



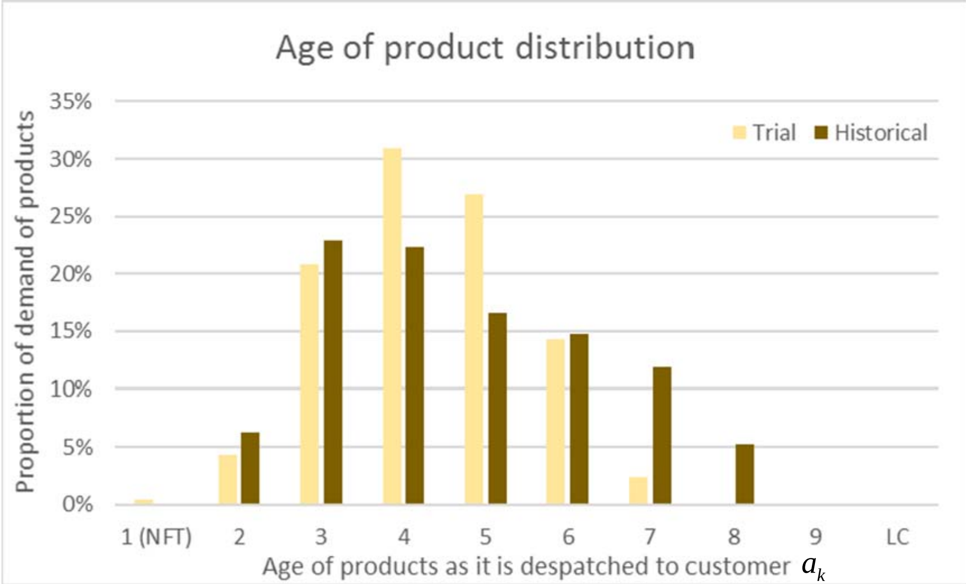




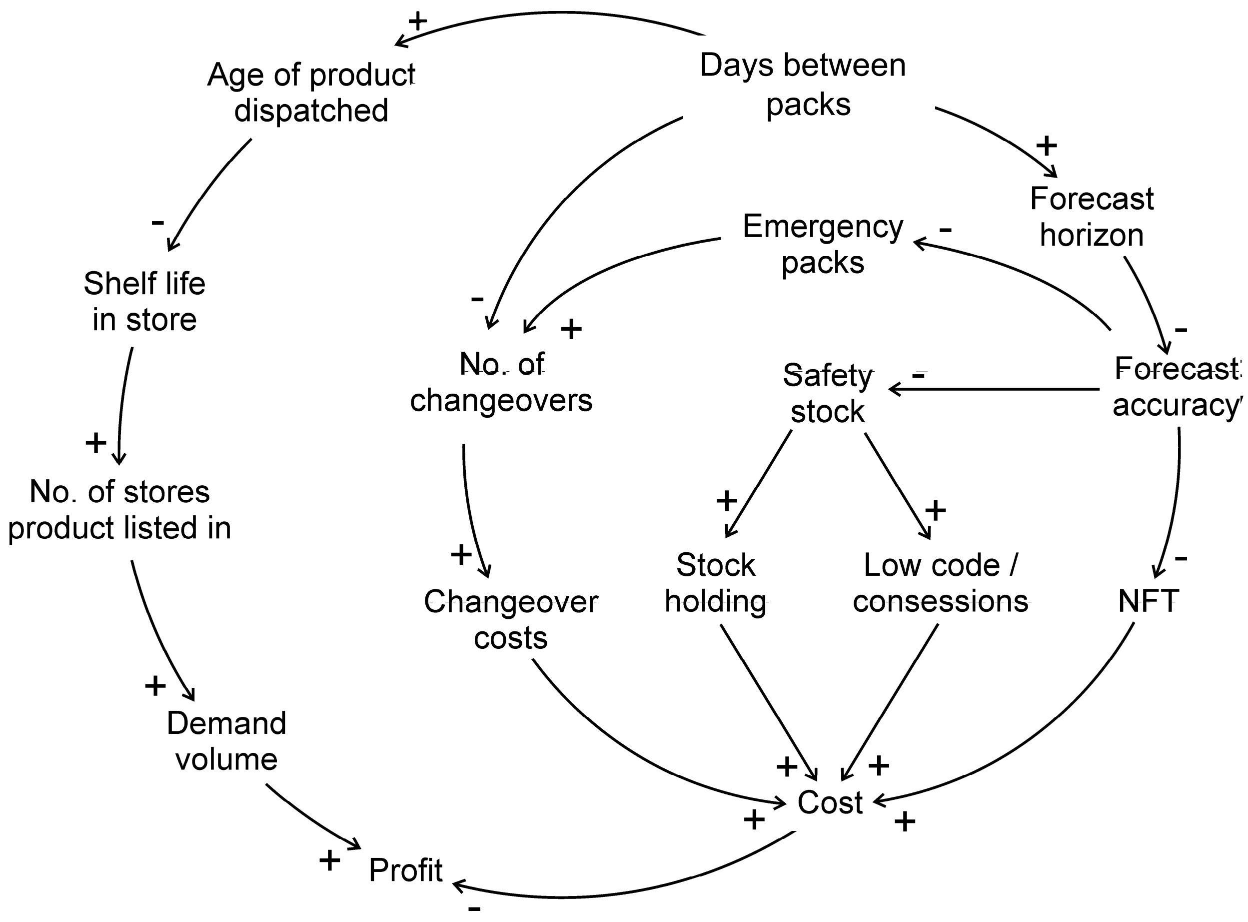


Distribution of the age of the product when it is despatched to the customer

- As product is despatched on a first-come-first-served basis, we are able to model the a_k age, of the product on the day it is despatched to the customer.
- **NFT. Need for tonight.** The company wishes to avoid despatching product on the day it is made (so that it can be chilled properly)
- **LC. Low code.** Product that is 10 days old has to be discarded (or sold as a concession)



The pack frequency strategy

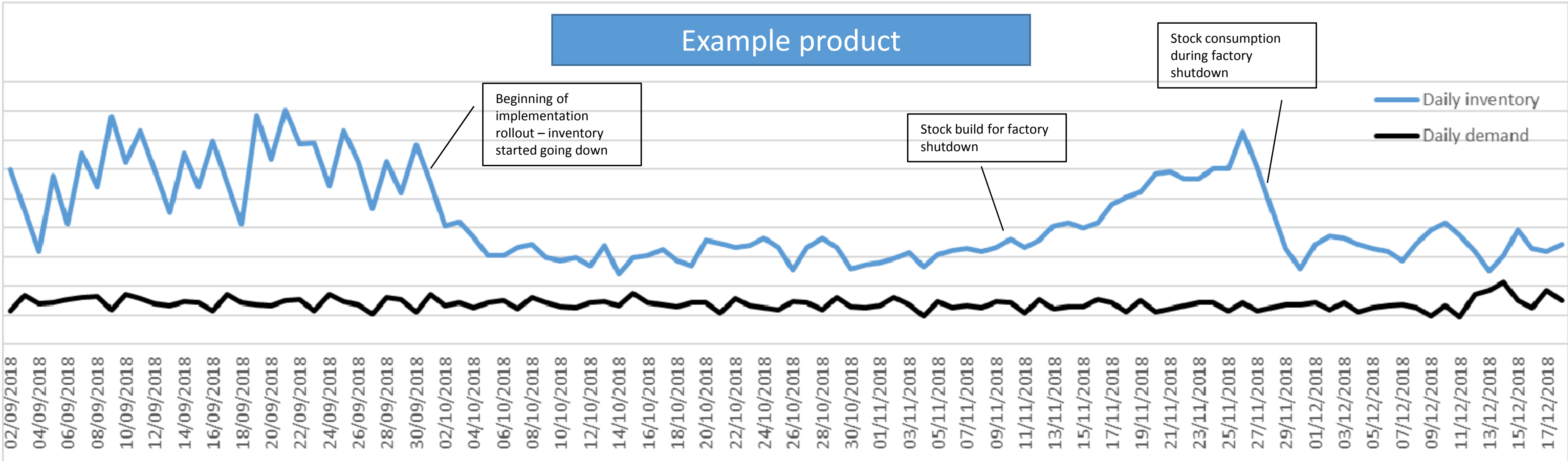


Rolling out to all 55 products within a single factory

- We identified that most of the products should be forecasted with exponential smoothing, a few with Holt-Winters methods, and a small number of products should be manually supervised.
- We also decided to link the production planning system to the 4 day shift pattern.
- This allowed us to defined the sequence of production for all products in every four day shift creating a high degree of certainty in the work that needs
    - More predictable changeovers
    - Fixed, and optimised, production sequence
    - Easier to put the “aces in their places”
    - Easier to schedule maintenance
    - A degree of clam and certainty has replaced the urgent panic that used to exist
    - Many coordination tasks have now disappeared

55 product factory rollout performance review

	Rush orders in cases	Fill rate	Fill rate (if no rush orders)	Out-of-date stock in cases	Total number of packs
Historical company performance	344,303	99.0%	95.5%	780,907	5080
Expected performance (from simulation and analysis)	81,145	99.1%	99.1%	14,566	5332 (+5%)
Actual company performance from rollout	29,944 **(-91%)**	99.7%	99.6%	12,361 **(-98%)**	5433 (+6.9%)
ALL NUMBERS ARE ANNUALISED					



Age of products

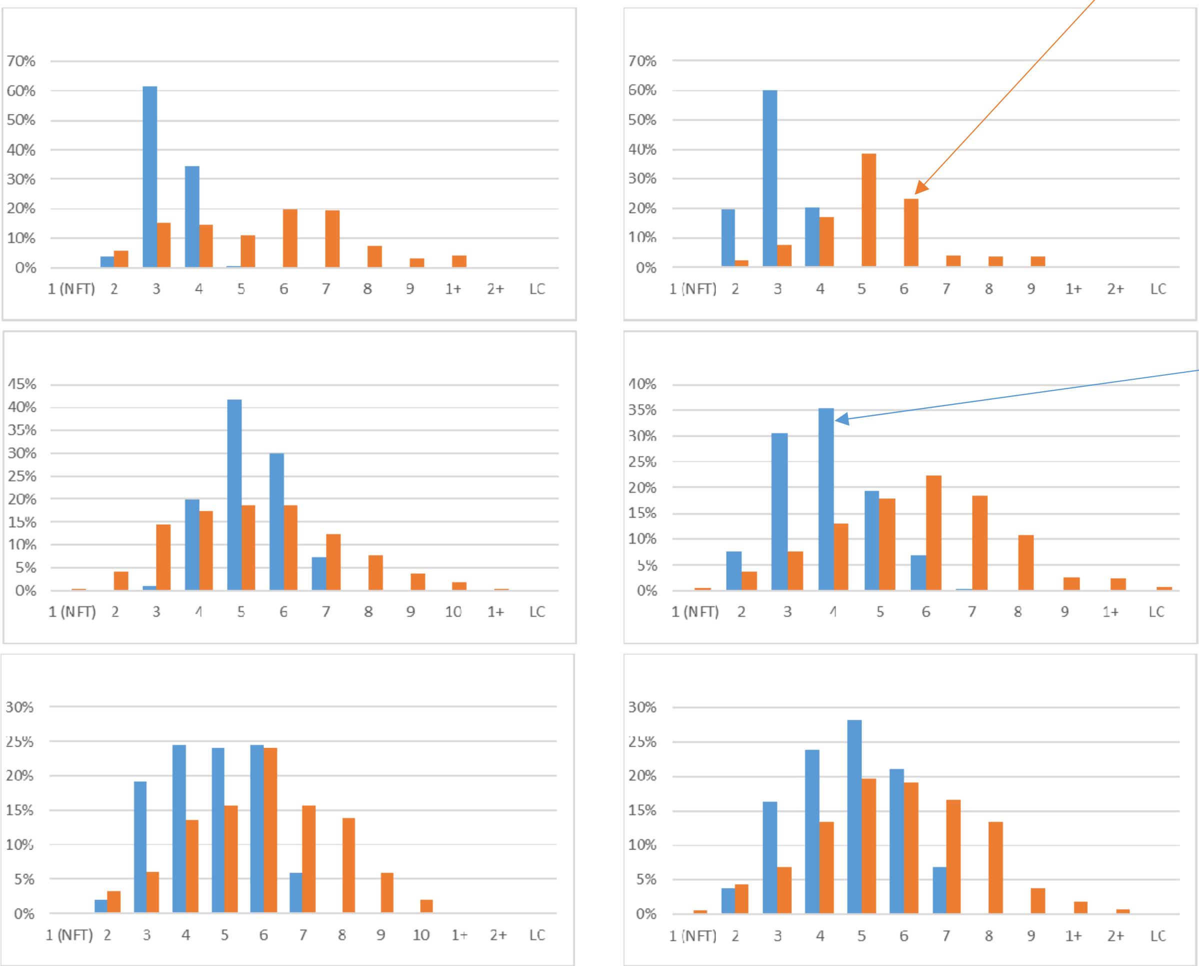
Performance 12 months ago

Products packing everyday

Products packing every 2 days

Our performance

Products packing every 4 days



In the next instalment…

- For the last 18 months we have been working with a UK dairy manufacturer on a 2 year forecasting, production planning, and supplier replenishment project
- We have mapped 27 products, and won approval to improve their business processes
- We have tested our recommendations to forecast and plan the production and replenishment for a group of 9 products (i.e. we are actually creating the forecasts and schedules)
    - The nine products share a common base ingredient are in a range that goes to one customer and all share the same production equipment and labour
- We have implemented our forecast and production planning approach to an entire factory (producing 55 products)
- We are currently in the middle of rolling-out solution to a factory of 400 products
- We are also doing the fieldwork to identify improvements in the supplier replenishment process.

Sept 2017. Project start

Nov 2017. Mapped 27 different products

April 2018. Pilot study on a single product range of 9 products

Oct 2018. Complete control of a factory producing 55 products

April 2019. Complete control of a factory producing 400 products

May 2019. Mapping the replenishment process with suppliers

June 2019. Improving the supplier replenishment process

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