POLITECNICO DI TORINO

DEPARTMENT OF ENGINEERING AND MANAGEMENT

MASTER'S -DEGREE THESIS IN SUPPLY CHAIN MANAGEMENT

System Dynamics Simulation of the Effects of the DDMRP Implementation.

The Whirlpool EMEA Case Study.

Academic Supervisors :
Prof.ssa *Anna Corinna* CAGLIANO
Prof. *Fabio Guido Mario* SALASSA

Company Supervisors:
Matteo COPPOLA
Laura Beatrice BRUKARZ

Author:
Jacopo DI GIACOMANTONIO

A.Y. 2021 / 2022

Is equilibrium

beauty?

POLITECNICO DI TORINO

Abstract

DEPARTMENT OF ENGINEERING AND MANAGEMENT

System Dynamics Simulation of the Effects of the DDMRP Implementation.

The Whirlpool EMEA Case Study.

by Jacopo DI GIACOMANTONIO

Firms must rely on their Supply-Chain to execute their strategies and cement their competitive advantage in markets that rapidly change as the results of globalisation, emergence of viral “fast-dying trends” powered by social medias and the proliferation of products designed for shorter life cycles. Moreover, modern times revealed to the general public what happens when the “invisible hand” of supply-chains suddenly stops moving things around. The surge of the global COVID-19 pandemic in 2020 made the world distant again, showing how fragile were the supply-chains used to run the world smoothly, and still nowadays affected by the global supply shortage.

In this study a *first-of-a-kind* to the author knowledge **System Dynamics model implementing the innovative inventory management policy of the Demand Driven Material Requirement Planning (DDMRP) is developed**. In the proposed model, a systemic approach is adopted to assess and model the typical processes involved in a company trying to cope with the *stock management problem*, as defined by J.Sterman in “*Business Dynamics”*. Hence, eight interconnected modules are devised to describe the dynamics of the *Order Fulfilment function, Demand forecasting, Average Daily Material Usage (ADU) forecasting. Finished Goods Inventory management, Raw Materials Inventory management, Direct Procurement, Sales and Operation Planning,* and *Financial reporting*.

The resulting model was intensively tested against two publicly recognized datasets about traditional inventory management and DDMRP one, in addition to many small tests run by the author to fine-tune the model. Very simple univariate and multivariate sensitivity analysis are also applied trying to define the most impacting DDMRP performance drivers. The study ends by testing the final version of the model against the data pertaining to the business case study of Whirlpool. In May 2021, Whirlpool EMEA leadership, faced by an overshoot in the raw materials inventory at one of its key Italian plants, the Cassinetta (VA) plant, responded by deploying its pilot implementation of DDMRP.

Table of Contents

Chapter 1

The Dynamic Context of Supply Chains

" The supply chain stuff ... really ***tricky*** *"*
cit. Elon Musk

Firms must rely on their Supply-Chain to execute their strategies and cement their competitive advantage in markets that rapidly change as the results of globalisation, emergence of viral "fast-dying trends" powered by social medias and the proliferation of products designed for shorter life cycles. Moreover, modern times revealed to the general public what happens when the "invisible hand" of supply-chains suddenly stops moving things around. The surge of the global COVID-19 pandemic in 2020 made the world distant again, showing how fragile the supply-chains used to run the world smoothly were, and still nowadays affecting the input availability worldwide. After costs have been compressed to the extreme building the most efficient productive systems thanks to Lean and Kaizen approaches, no additional radical growth is attainable by firms in the market if not by means of proper Supply Chain Management. In this chapter, a brief introduction of what supply-chains are, how they are structured and what are the biggest challenges they must face, is given. The chapter concluded by introducing the Walmart and Zara case studies to illustrate that communication and collaboration play the key success factors to attain sustainable competitive advantage in the new V.U.C.A. world. Finally, an overview of the mostly adopted KPIs adopted to benchmark supply-chain performances is provided.

1.1. What are Supply Chains

As simple as it might sound, *supply-chains* are established every time a couple of entities start sharing *resources and information flows* to pursue the common final aim of *satisfying a downstream final customer need*.
In reality, supply-chains easily get more complex, presenting *multi-echelons multi-directional structures* that can span the globe, also called *logistic networks*. Is indeed typical to find the following parties participating in a supply-chain

1. **Raw material suppliers,** representing all agents sourcing raw inputs and commodities (e.g foundries, miners, chemicals producers, ect.) to the downstream nodes ;

2. **Original Equipment Manufacturers (OEM),** representing all agents involved in the production of goods and services used as components from a downstream node ;

3. **System-integrators,** also known as *value-added resellers* (VAR), which assemble semi-finished products sourced from OEMs into *sellable-to-public finished products* , after eventually having performed additional manufacturing operations ;

4. **Wholesalers,** representing all Business-to-Business (B2B) distribution intermediaries responsible for mass serving different regional markets through retailers, selling items at a lower-than-market-clearing price ; and

5. **Retailers,** also known as *Point-of-Sales* (POS), representing all Business-to-Consumer (B2C) agents directly selling finished goods to customers in rather small quantities, thus applying final pricing, marketing promotions and delivery.

Obviously, being the supply-chain landscape extremely varied, such a classification is not a rigid one and different agents might decide to play multiple roles in the chain for many strategic reasons, verticalizing from manufacturing down to retailing.

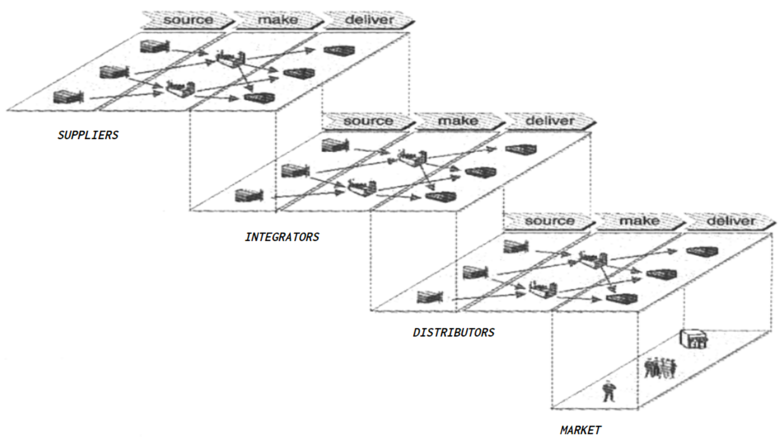


Fig.1.1. *Typical multi-echelon structure of supply-chains.*

The specific structure of the logistic network tends to accommodate the industry cost structure, seeking a *minimum cost configuration.* Thus, in general terms, the smaller the difference between procurement, transactional and manufacturing costs gets with respect to the total costs of all goods movements and material transportations the sparser the networks becomes. For instance, the Walmart logistic network is an highly decentralised one, characterised by many low-cost and small-sized *Stock Keeping Units* (SKU), sourced by mainly local vendors, that can easily fit in large quantities on a *full-truck load* as a results of a *milk-run*, whereas the Boeing logistics network is a highly centralised one, characterised by many expensive items whose production is outsourced to specialised OEMs that ship their portion of the aircraft back to the single assembly plant from where the aircraft is then shipped. Such considerations are considered during the strategic activity of *network planning* held when designing the company supply-chain.

Along with network planning, a panel of other activities are executed *as part of* the *Supply-Chain Management* (SCM), namely

1. **Procurement,** grouping all activities required to execute strategic selection of suppliers, supply-contract negotiation and enforcement, specification development and good-receipt.

2. **Order Fulfilment,** grouping all activities required to collect, prioritise and define *promised delivery dates* and fulfil customer orders.

3. **Inventory Management,** grouping all activities required to define *target inventory levels* required to reliably *sustain desidered service levels* and release the inventory *replenishment plan* based on a specific *inventory control policy*.

4. **Warehousing,** grouping all activities required to properly unload received material, perform inbound quality controls and warehouse management to optimise pick-pack-and-ship of finished goods.

5. **Transportations,** grouping all activities required to define and schedule the proper delivery route (e.g. Rails, Parcel, Air, ect.) for all inbound and outbound flows.

6. **Planning and Demand Forecasting,** grouping all activities required to define productive capacity requirements, locate facilities to minimise transportations costs or time-to-market, network planning and forecasting future demand requirements so as to produce a viable *production plan*.

7. **Customer Support,** grouping all activities required to manage after-sales events such as goods returns, warranty issues or functional troubleshooting.

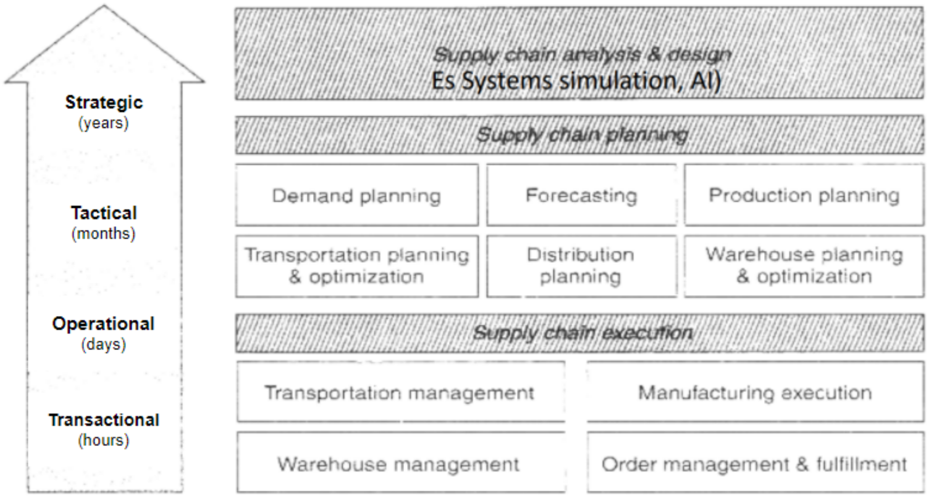


Fig. 1.2. *The different horizon covered by different SCM functions, extracted from F. Dallari "Rinnovare La Supply Chain"*

Finally, as anticipated above, an open debate regards "where to draw the line" separating *Logistics* from SCM. Indeed, in the early days of supply-chains, the word *logistics* was rather used to refer to those activities performed so as to manage inbound (e.g. material receipts) and outbound flows (e.g. distribution), thus focusing mainly on the operational aspect of supply-chains. According to the Council of Supply Chain Management (CSCM) Professionals

Supply-Chain Management *"encompasses the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities. Importantly, it also includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third party service providers, and customers. In essence, supply chain management integrates supply and demand management within and across companies"*, while

Logistics management *"is that part of supply chain management that plans, implements, and controls the efficient, effective forward and reverse flow and storage of goods, services and related information between the point of origin and the point of consumption in order to meet customers' requirements".*

Thus logistics is seen as a subset of SCM. A review of the different opinions about such a debate lead to four major philosophies

1. **Traditionalists,** whose position SCM as the subset of logistics practices pertaining to the "*logistics outside the firm*" ones.

2. **Unionists,** the position taken by the CSCM where logistics is treated as part of SCM but is not limited to intra-company activities rather it includes activities required to couple with external companies effectively.

3. **Intersectionists,** suggest that only partial overlapping between logistics and SCM occurs, being function like marketing and purchasing intrinsically different from operation management.
4. **Re-labelling,** where logistic is simply completely replaced by SCM, being both related to the same things.

The position of the author about such a debate is described by Fig.1.3, being the *unionists* approach considered as the most representative of current company practices.

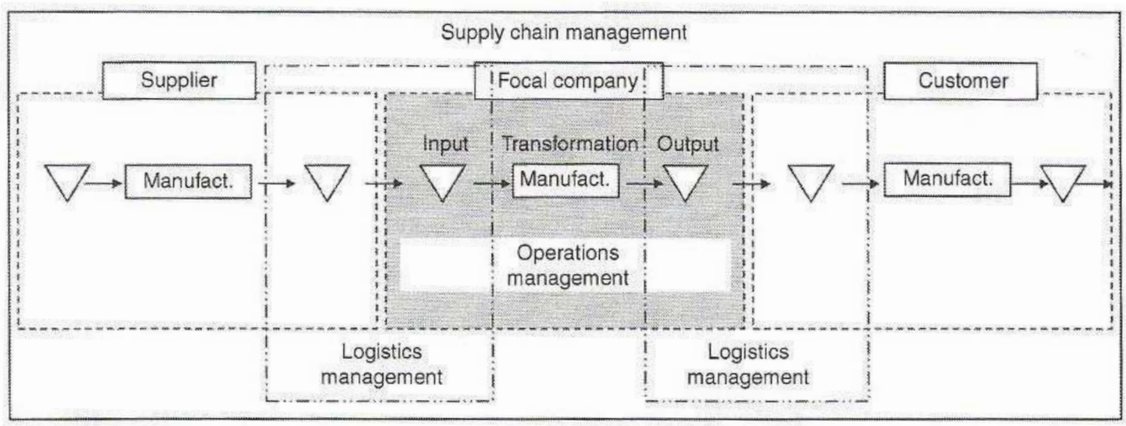


Fig.1.3. *The functional structure of Supply-Chain considered in this study, extracted from C.Rafele, et al, 2020.*

Hence, the list of activities considered in this study as part of logistic are:
1. Material reception from suppliers,
2. Warehousing,
3. Inventory Control,
4. Pick-Pack-and-Ship,
5. Transportation and last-mile delivery,
6. Reverse logistics.

Such a conclusion is also supported by the 6-months internship experience held by the author in the Whirlpool Sourcing Excellence Procurement Office during early-2021.

1.2. Main challenges in Supply Chain Management

Being final customers the *unique origin of revenues* in the system, the main goal of all supply-chains should be to maximise the total value extractible from them, considering that such value must be sufficient so as to reward the whole chain with profits. Assuming customer willingness to pay for a certain product fixed, to achieving such a goal implies pursuing two basic objectives
1. **Minimising "to-shelf" costs,** optimising costs of all activities run by each node of the chain, and

2. **Maximising product availability,** guaranteeing *unitary service levels* every day.

Thus the *supply-chain management problem* can be visualised as a classical *optimization problem* where two objective functions Z_1 and Z_2 must be optimised concurrently under a set of constraints defined (and controlled) by each agent in the chain. Being classical optimization problems usually considering a single objective function at the time, already at this level the complexity of the problem emerges. Moreover, opposing actions seem required to achieve either goal. That is, *guaranteeing higher service levels traditionally requires an increased inventory commitment*, thus an increase in working capital requirements. Moreover, trying to disaggregate such a problem *at the single company level* shows that in order to maximise the own position an additional set of smaller optimisation problems emerge for each company function, with its set of constraints. Finally, extending such disaggregation to all nodes in the chain would let *opposite incentives among the players emerge* which, in conjunction with typically *incomplete information* available to all agents, make the pursuit of a *global optimum* an extremely hard one to reach. With modern supply-chains getting longer and spread globally among many cultures, an appropriability threat of such profits emerges. On the other hand, in the pursuit of cost reduction, the 1980's saw the emergence of new managing strategies like *Just-in-Time* (JIT), *Lean* and *Kanbans* that positively affected the cost function of many companies. However, nowadays an efficiency plateau seems reached, where the only new opportunities for additional cost reductions seem locked under a missing *systemic-view* of the chain by its actor (Simchi-Levi). *Coordination* is thus the first biggest challenge to tackle for effective SCM.

A major cause of inefficient coordination in supply-chain is instead created by the necessity of all players to *forecast future demand,* letting *uncertainty management* become the second biggest challenge for effective SCM. As explained in Simchi-Levi, Chapter. , the *three basic principles of all forecasts* states that

1. *forecasts are always wrong,*
2. *the farer their forecasting horizon is, the less accurate they are,* and
3. *aggregate forecasts are always more accurate than ones on individual items*

Hence, with *Customer tolerance times* constantly getting shorter, when overnight free-deliveries are offered by big worldwide retailers such as Amazon, there is no chance for manufacturers to pursue any *targeted service level* without committing in advance to certain production volumes. Immobilisation of capitals in machinery, labour and raw materials inventory thus must be run on a bet causing huge financial risks and market frictions among the players.

On top of these, the following are considered by Simchi-Levi tough SCM open issues

1. **Proper inventory control,** questioning whether inventory must always be a direct consequence to supply and demand uncertainty and whether agents should always exactly follow forecasts.

2. **Optimised warehouse localisation,** which still represents a hard optimisation problem especially if extremely fluctuating demand trends are considered.

3. **Optimised distribution routes,** questioning what are the limits to centralisation and decentralisation strategies and to which are their effects on stock keeping costs and transportation costs.

4. **Strategic partnering,** questioning why effective supply-chain integrations seems only applicable by big companies and why are the key informational exchanges required to make it work.

5. **Outsourcing control,** questioning how to unequivocally execute outsourcing contracts and share of intellectual property especially in the case of off-shored production.

6. **Optimised product designs,** questioning whether product redesign can be implemented so as to minimise the impact of new product introduction on current inventory levels and obsolescence risk.

7. **Informative decision-support systems,** questioning which data are really significant for SCM and which can be ignored.

1.3. The V.U.C.A. environment we live in

Coined by the *Demand Driven Institute* (DDI), the term V.U.C.A. briefly summarise the current status of most supply-chains:

1. **Volatile,** because demand presents extreme, sudden fluctuations, with many products having shorter life cycles. Consider for instance a suddenly exploding demand trend created by the viral spread of a trend on social media and the internet, or the conventional iPhone 1-year refresh cycle. In Sterman, Chapter 18, an example from the computer and electronics industry is reported where planners must concurrently need to forecast sales for a new product introduction while planning the ramp-down phase of material procurement and production during the peak-adoption phase of the product life.

2. **Uncertain,** the high information asymmetry maintained by many players in the chain, generating bullwhip oscillations, gets coupled with the basic principle of forecast (*all forecasts are wrong)* cluttering the view on the system with artificial noise. Moreover, being modern supply-chains mostly decentralised, sources of threats may come from multiple places.

3. **Complex,** globalization scattered the logistic network among many nodes making the already non-trivial task of synchronisation, control and alignment of incentives along the chain even tougher by means of cultural aspects, languages or simply timezones.

Moreover, the number of individual SKUs managed by the same company increased substantially so as to deliver multi-regional market segmentation.

Fig. 1.4. *Main air-carriers logistic routes, extracted from C. Rafele et al, 2020.*

4. **Ambiguous,** among the vast amount of data available, companies struggle to grasp what really matters and what is noise instead. The singular case of fake-news spread and the dismaling pursuit of proper fact-checking by social media providers such as Facebook or Twitter provides an example.

The recents events (e.g Covid Crisis, The Suez Canal EverGreen incident, the Ukrainian conflict) largely proved the VUCA nature of modern supply-chains and added to the list the concept of *resilience.* Pursuing cost reductions to the extreme in the name of "*lean the processes"* made supply-chains fragile and rigid at their core. *Adaptive systems*, where inventories are managed as assets and not as costs, and where supply-chains act as *shock absorbers,* are rather required to guarantee performances in an ever changing environment.

1.4. The Bullwhip effect: what customers don't see

Most of the time, retailers, being directly exposed to customers, are the only agents in a supply-chain fully aware of what the real demand for a product is and whether any kind of trend is foreseeable. On the other hand, being the retailer trying to protect himself from stock-outs driven by unforeseeable variability in either supply or demand, its applied re-order logic will *hide* the real product demand to the upstream layers of the chain, adding variability. In a chain where only retailers own real demand data, every other node would be forced to apply *forecasting methods* against the information stream received by the dowside layer, applying *first-order smoothing* of such trends so as to avoid nervousness. However, such practices under those conditions, in turn, just apply wasteful re-elaboration of the initial signal coming from customer orders, adding at each stage more and more variability. This condition is a well-known one in supply-chain management as of *bullwhip effect.* The APICS dictionary, redacted by the International Association for Supply Chain Management (ASCM), defines the **bullwhip effect** as:

" An extreme change in the supply position upstream in a supply-chain generated by a small change in demand downstream in the supply chain. Inventory can quickly move from being backordered to being excess. This is caused by the serial nature of communicating orders up the chain with the inherent transportation delays of moving product down the chain. The bullwhip can be eliminated by synchronising the supply chain. "

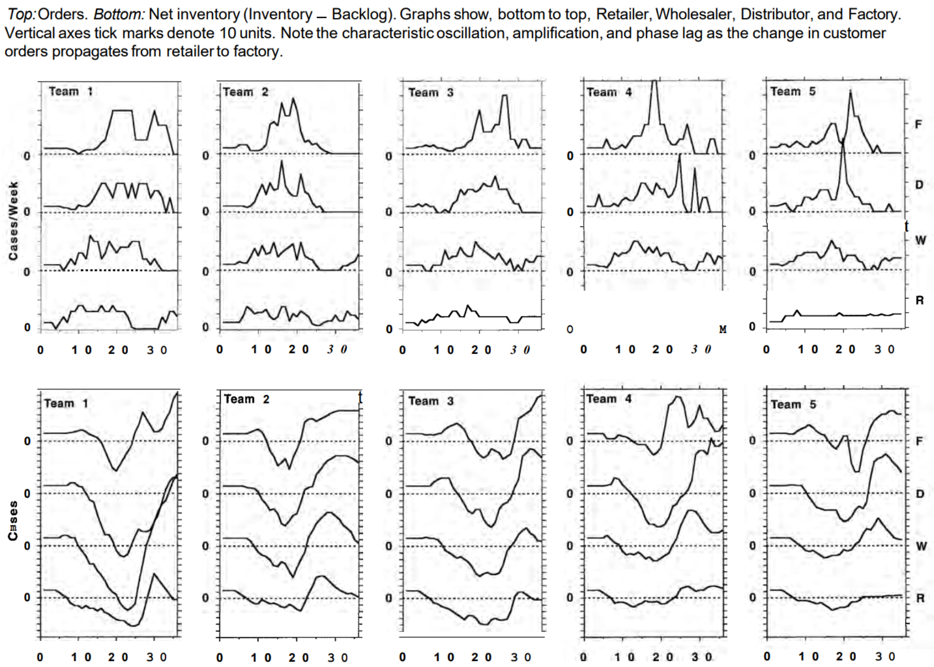


Fig. 1.5. *Bullwhip effect emerging from the famous MIT Beer Distribution Game, extracted from Sterman, 2013..*

Thus, if real customer data were to be visible to all nodes of the chain, each node would have *complete information* to apply appropriate forecasting. Among the many reasons why retailers would not share their knowledge about customer orders, the most relevant ones pertain to strategic factors. Other artificial sources of variation inducing bullwhip scenarios includes (but are not limited to) events like

1. **Batch ordering**, where the downstream node prefers to release big lumpy orders rather than small smoothed ones so as to reduce their order-issuing costs,
2. **Materials seasonal promotions**, where downstream nodes buy greater-than-necessary quantities sold at the lower price so as to stock-up and reduce the direct material costs of its future inventory (thus increasing returns).
3. **Allocation threats**, where multiple downstream nodes release inflated "phantom orders" in order to steal upstream node capacity to competitors, or to reduce the probability of their orders to be rationed during periods of shortages.

Finally, Simchi-Levi, Chapter 5, proposes a formulation to quantify the bullwhip-effect showing how the longer and less collaborative the chain is, the greater the *amplification ratio* in order estimates between two subsequent layers gets. An important finding emerging from it is that *upon any kind of echelon-transmission some additional variability is always added to the initial signal*. Thus, collaborative strategies such as *Vendor Managed Inventories,* or *reshoring,* coupled with technologies like *Electronic Data Interchange* (EDI) are designated as capable of attacking bullwhip spread, but could never completely cut it off.

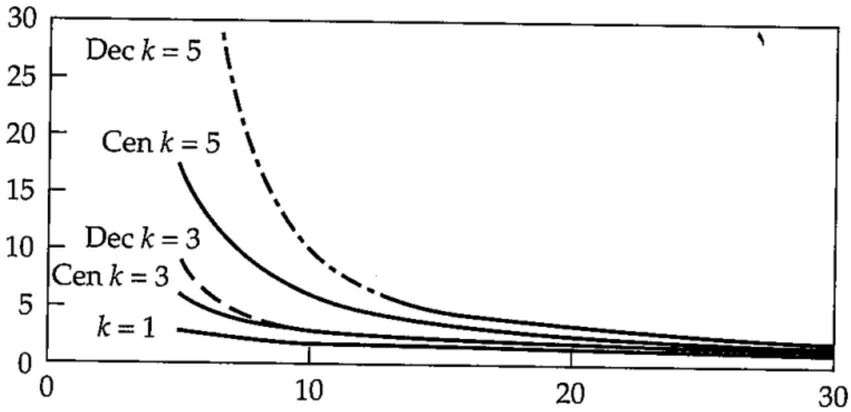


Fig. 1.6. *Increase in order variability in centralised and decentralised supply-chains, extracted from Simchi-Levi.*

1.5. The competitive advantage derived from Supply-Chains

In 1985, *Michael Porter*, the father of modern corporate strategy development, released the innovative concept of *value chain*, as opposed to the conventional value-added and costs analysis, to describe companies as a set of primary and supporting *value activities* organised together to produce a *margin* as proof of the company's capability of creating *competitive advantage*.

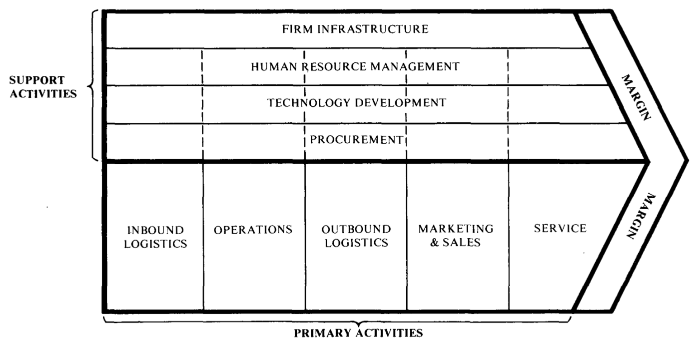


Fig.1.7. The *Porter* value chain, extracted from Porter.

In the value chain, logistics figure as primary activities, essential to organise unrelated components into sellable products, and it is supported by procurement. The key concept for SCM derived from the Porter value chain model is that *value chains belonging to the same channel can vertically influence each other's performance to produce a margin*. Thus, planning operations is such a way that the downstream node is eased in its capabilities of generating margin, it is of interest to the upstream nodes too. Indeed, if the downstream node suffers of *reputational damage* incurred by means of its suppliers poor cooperation, such a node will be struggling competing in the market, eventually losing market share, cascading back to its suppliers now receiving less orders. Following, some relevant case studies are briefly summarised to address the potential gains from integrating the supply-chain toward margin generation.

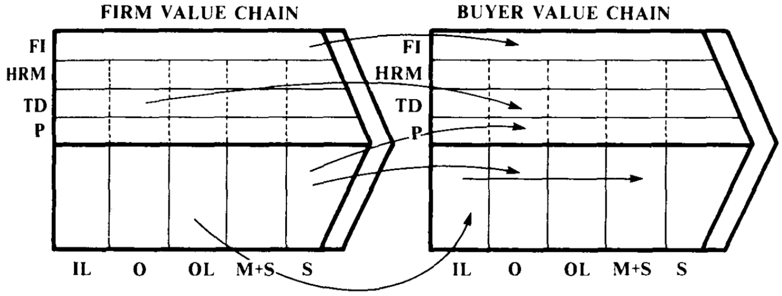


Fig. 1.8. *Vertical interaction between value chains, extracted from Porter.*

Ironically, in 2015 the world' best scoring company in terms of revenues was *Wal-mart Stores Inc.,* the giant of the US discount retailing industry whose motto fiercely claimed "*everyday low prices*" (EDLP) since 1972. Wal-Mart strategy focused on replenishing "the forgotten" small suburbs at the lowest prices possible. The problem with such a strategy was given by the distribution channel which did not urge to serve such a "niche". Thus, in 1970 Wal-Mart went public and integrated downstream building its own distribution centres to efficiently serve its local stores and slowly expand its business to the bigger US cities. With time, such a move revealed a winner, letting Wal-Mart become the most attractive partner for manufacturers (e.g. Procter & Gamble) who wanted to gain instant access to a large customer pool exploiting Wal-Mart distributed presence in all 50 U.S. states. Such extended demand gave Wal-Mart extreme bargaining power, which it fully exploited to pursue the EDLP goal by squeezing vendors' margins to the extreme. In the 1990s, when EDI became available, within 2 years Walmart extended it to all its US partners. Using EDI, vendors could log into Walmart "*Retail Link*" portal and check the status of their items *on a store-by-store basis*. Such practice allowed suppliers and manufacturers to synchronise their demand projections under a collaborative planning, forecasting, and replenishment scheme, resulting in Walmart achieving faster replenishment, lower inventory, and a product mix more closely tuned to the local customer needs. Unsurprisingly, the 1996 Wal-Mart expansion attempt in Brazil suffered the lack of such integration with the local vendors along with other cultural frictions.

Explaining the *Zara* business model in a sentence,]osé Maria Castellano Rios, Inditex CEO quotes *"the original business idea was very simple: link customer demand to manufacturing, and link manufacturing to distribution".* Zara competes in the fast-fashion industry, where customer demand is created by young, fashion-conscious city dwellers whose purchasing decisions are mainly influenced by "fashion misses and rock stars" launching trends that tend to fade some months ahead. Thus, Zara aims at delivering currently in-trend fashion rather than old stocked patterns, with a vision of "*letting people feel comfortable* *wearing Zaras even at weddings*". To achieve that, Zara executed a *divide-et-impera* integration strategy of its supply-chain, in-house centralising all the automatizable parts of the process (e.g. fabric patterns cutting) and subcontracting parts of its productive process to small spanish and portuguese local manufacturing firms, such as sewing. Prior to seasonal-production, new designs were occasionally shared with third-parties so as to let them prepare samples. This infrastructure would potentially produce a continuous stream of fabrics moving between the 21 Zara factories and its subcontractors, allowing Zara closing a style production within 10 days from its first order release. Finally, extensive responsibilities were given to store managers which were empowered to request items from a collection based on their sensations about local sales, whereas unsold items were recollected for possible reshuffling.

1.6. Key Performance Indicators in Supply Chains and Logistics

Being cost reductions and product availability the main pursued objectives in a supply-chain, the *Key Performance Indicators* (KPIs) usually deployed to monitor them include (but are not limited to) the following list

1. **Service Level,** the probability of not stocking out during a replenishment cycles;
2. **Direct costs,** *Materials costs; Transportation costs; Quality control; Manufacturing costs; Labour costs; Distribution costs and taxes;*
3. **Indirect Costs**

   Shortages costs, the costs associated with stock-outs recognised by lost sales plus all sunken production costs attached to them;

   Transactional costs, the cost of enforcing procurement contracts and control the supply base;

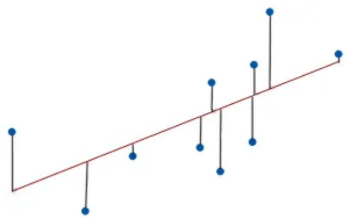
   Shared resource usage;y, such as electricity, or storage space;
4. **Return on Assets (ROA),** the amount of profits generated by asset utilisation; In the supply chain[R] context it can be evaluated as

$$ROA = \frac{EBITDA}{Average\ Inventory}$$

   Being EBITDA the *Gross Profit Margin*;
5. **Inventory Turnovers,** the velocity at which inventory "turns" and fully replaces itself. It measures the firm's ability to exploit its inventory to generate profits. The optimal value of it depends on the reference industry evaluated, but in general products with higher margins and faster lead times should have low turnovers..

$$ROA = \frac{COGS}{Average\ Inventory}$$

6. **Forecasting Error,** the historical deviation of forecasts from actual demand. It can be measured in multiple ways, being the *Mean squared Error* (MSE) typically used in conjunction with the *coefficient of determination* R^2 when applying linear regression.



$$MSE = \frac{\sum(y_i - \hat{y}_i)^2}{n}$$

Fig. 1.9. *Representation of the MSE*

7. **Warehouse capacity,** the maximum available storage space;
8. **Customer Satisfaction**, it represents a metric made by the aggregation of multiple aspects, being customer satisfaction driven not only by proper delivery times but also by the final product quality. In this study this metric is evaluated as the portion of cancelled orders over the total.
9. **On-time deliveries,** the number of orders shipped within promised dates;
10. **Days of Coverage,** the days-equivalent of demand coverage kept as inventory. It provides an estimation of how long the firm will be able to satisfy demand if inventory replenishment suddenly stops.
11. **Obsolescence Risk,** the amount of stored materials and finished goods that risk to become obsolete and must be scrapped.

Chapter 2

Inventory Management Policies

*" The **inventory**, the **value** of my company,*
walks out the door every evening "
cit. Bill Gates

Inventory is the tool in the hand of firms to cope with uncertainty within supply-chains, indeed figuring on companies' balance sheets as an *asset*. Therefore, as for all assets, it has the potential of generating profits if managed properly. However, inventory is rather widely perceived solely as a bleeding *cost* that must be "*minimised ... no costs"* in order to properly pursue supply-chain management. In this chapter, this attitude is challenged and the conventional strategies available to managers to control their inventory are presented. Then, the DDMRP methodology, the main character of this study, is carefully detailed for each of its implementation phases.

2.1. What is Inventory?

In the United States (US) more than a trillion USD of companies assets are immobilised as inventory (Simchi-Levi, Chap.2). In 1984, *General Motors* (GM) total inventory was estimated for 7.4B USD, of which 70% in *Work-in-Process* (WIP) material. GM total freight cost to move such imponent quantities topped 4.1B USD. Thus it is understandable that, for managers inventory typically represents just a bleeding financials to contain and possibly minimise. Such managerial *beliefs* drove the rapid diffusion of different supply-chain strategies mostly focusing at *redistributing the inventory along the chain*, such as Vendor Managed Inventories (VMI) or the Lean "proximity network". However, because such strategies must deal with the VUCA environment mentioned in Chap.1, they hardly achieve their goal, rather making supply-chain more fragile to disruptions. Indeed, the main role of inventory is to *cope with uncertainty in demand and supply* and *synchronise them*. Many might be the cause of such uncertainty (Chap.1), being long-term demand forecasts, shortening products' life cycles and high product variety in the market, seating first row. Hence, the extreme pursuit of inventory minimisation *provides a very simplistic view of SCM* (Simchi-Levi). Instead, the real goal of inventory must be to have it

1. in the right *quantities*,
2. in the right *locations*,
3. at the right *time*, so as to
4. *minimise* the total "to-self" *cost*, while
5. fully *satisfying customer* orders. (Simchi-Levi).

Unfortunately, solving such a *multi-objective optimization problem* requires challenging the traditional trade-off between *service level* and *inventory cost*. Even if they are always *precisely wrong*, forecasts still generate advantage in a VUCA environment and cannot be fully deprecated. Precisely, they let supply-chain managers look toward the right direction when planning future inventory requirements. Indeed, if forecasts were exactly right all the time, inventory was not needed instead. *Managing inventory* thus became the key to execute adaptive-reactive strategies to survive in the VUCA environment (Castro, 2020).

2.2. Traditional Policies

As anticipated in Chap.1, essentially, inventories get critical when they

1. ***Stocks-out***, falling to zero or below generating shortages and starvation of upstream nodes and thus global service level reductions which translate into lost sales;
2. ***Overstocks***, accumulating in form of excess material, thus immobilising working capital in storage space and material that rapidly risks becoming obsolete while weighting on firm financial performances (e.g ROA, ROI).

The major causes of stock out are related to uncertainty on either supply and demand, as shown in Fig.2.1, materialising the impact of the VUCA world.

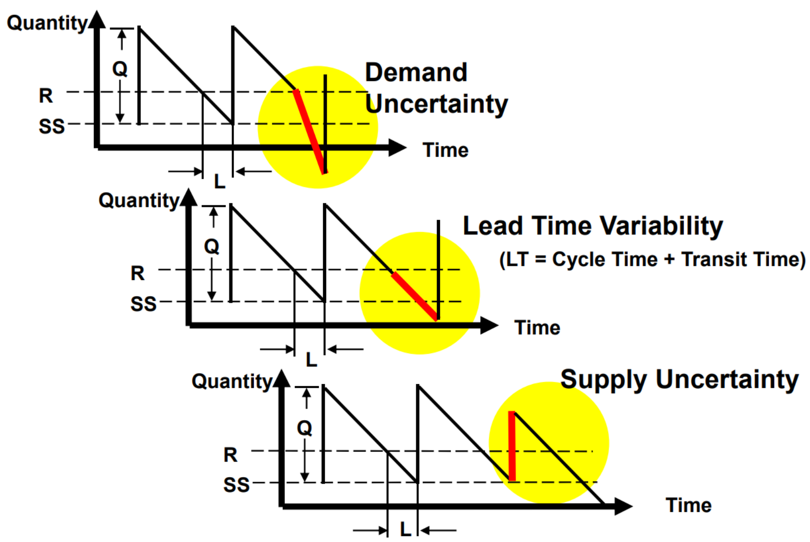


Fig. 2.1. *Typical causes of Stockouts, C. Rafele et al, 2020.*

The different strategies adopted by firms to stay away from those positions and protect from stock-outs are typically referred to as *Inventory Management Policies.* Such rules essentially define *how much* and *when* to order to prevent shortages but nothing is usually said regarding excess accumulation. Being the benefits generated by an improved inventory control of substantial impact to firm performance, a large variety of such policies exists, leveraging different features of supply-chains. However, they all designed to *minimise "to self-cost"*, and *maximise service levels,* requiring contextual input data, namely the estimates of

1. *Customer Demand trends*, relying on the *Best available Value* (BAV) at the time of policy setting,
2. *Replenishment Lead Times*, which real values might be only known when real orders get released,
3. *The SKUs impacted by the policy*, being them competing for warehouse space and budget,
4. *All cost drivers*, typically grouped into *ordering costs* and *holding costs* as seen in Chap.1, and
5. *Service Level targets*.

Summarising, all policies typically fall in either the category of

1. ***Fixed Order Quantities*** (FOQ), where orders of constant size (or multiples of a *minimum order quantity*) are released when the actual inventory reaches certain thresholds, or
2. ***Fixed Order Period*** (FOP), where orders of variable sizes are released on specific dates, defining what is also known as the *inventory review period*.

The adoption of any of these rules mainly depends on the time and costs required to the firm to fully review its inventory. For the purpose of this study only the *Economic Order Quantity* (EOQ) *rule* and the *continuously reviewed (R, Q) inventory policy* will be introduced. Both policies are applicable at each node of the chain while they do not guarantee network optimality. For a detailed review of inventory management policies the reader can consult Simich-Levi Chap.2.

To begin the concept of *Net Inventory Position* must be introduced. The Inventory position represents *the total net firm inventory in the chain* at any given time, thus the actual inventory available *on-hand* plus all the *open supply orders* waiting to be received from suppliers gets discounted by all the *pending backordered quantities*.

2.2.1. Economic Order Quantity policy

As intuiable by the name, the EOQ finds the best order size to minimise the total inventory made of two components: *holding* and *ordering* costs. The typical trade-off is shown in Fig. 2.2. As the bigger the order size gets, the more the firm can exploit bargaining power and scale economies in transportation, while the bigger the cost for stocking those orders it gets. Thus a minimum exists where the marginal cost increase from an additional unit equals the marginal benefit in order costs.

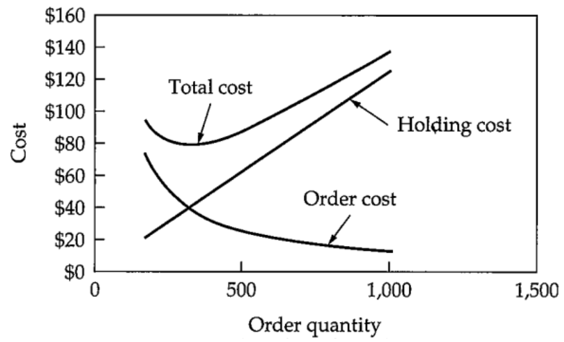


Fig. 2.2. *Economic Order Quantity cost trade-offs, Simchi-Levi.*

To achieve such optimality, EOQ assumes a rather simplistic environment where

1. demand is constant
2. every order entail a fixed cost K while the holding cost per unit is constant
3. there is no initial inventory in the system
4. the replenishment lead time is zero

Under such conditions the optimal *Economic Order Quantity* is given by

$$\frac{KD}{Q} = \frac{hQ}{2} \qquad Q^* = \sqrt{\frac{2KD}{h}}$$

producing a *chainsaw behaviour* as in Fig. 2.3.

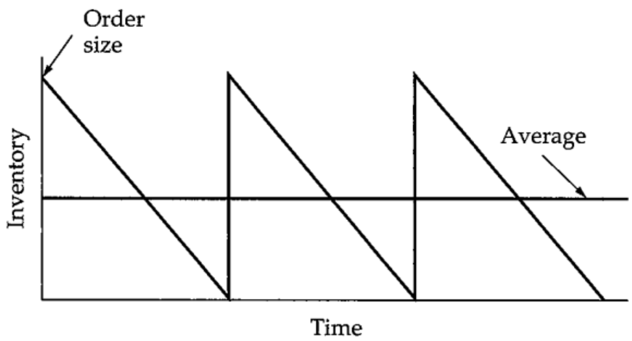


Fig. 2.3. *The EOQ policy behaviour over time, Simchi-Levi.*

2.2.2. (R, Q) reorder point policy

The biggest limitations of the EOQ rule are represented by the zero replenishment lead time assumption and the zero inventory position at the beginning of the period. Once those assumptions are relaxed, the best way to manage inventory is to *release an order that brings the inventory position back to a certain maximum level every time it falls below a certain threshold*. Such policies are thus called *reorder point policies* and their behaviour changes upon the frequency at which the inventory position can be reviewed, discriminating between *continous review policies* and *periodiccaly review policiy*. The typical behaviour of a continuously reviewed reorder point strategy is presented in Fig. 2.4 and it is fully described by the set of values (R, Q).

The *reorder point R* is set so as to synchronise an order release exactly when the current inventory on-hand is just enough to cover the *demand during the replenishment lead time* (DDR). DDR is a random variable, thus R is typically set so as to cover *average DDR* plus a certain degree of *unexpected demand peaks during replenishment lead time,* conventionally known as *Safety Stocks* (SS). Thus

$$R = DDR + SS = (\mu_D * RLT) + (z_{SS} * \sigma_D * \sqrt{RLT})$$

z_{SS} represents the *safety factor* and it is the connection point between (R, Q) policies and *targeted service level* (SL*). Indeed, being the service level equal to the probability of not stocking out *during replenishment*, z_{SS} must satisfy

$$Pr(DDR >= R) = Pr(DDR >= [(\mu_D * RLT) + (z_{SS} * \sigma_D * \sqrt{RLT})] = SL^*$$

Thus, to compute z_{SS} the real probability distribution describing DDR is required. As it can be imagined, knowing such a distribution is a non-trivial task, thus conventional theory invokes *a normality distribution assumption of DDR.*

Hence, the major limitations of traditional (R, Q) policies lie in the normality distribution assumption of DDR and the fact that orders received while the firm is stocked out are immediately lost. While in many industries customers accept a certain degree of delay after their order releas3, namely the *Customer Tolerance Time,* in some other industries like “fast-fashion” this condition does not necessarily hold.

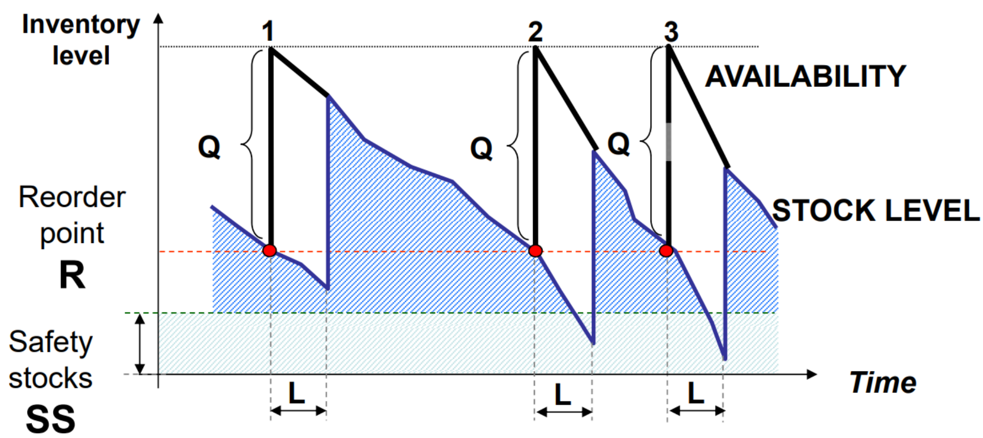


Fig. 2.4. *The (R, Q) inventory policy behaviour over time, C. Rafele et al, 2020.*

Z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
0.0	.50000	.50399	.50798	.51197	.51595	.51994	.52392	.52790	.53188	.53586
0.1	.53983	.54380	.54776	.55172	.55567	.55962	.56356	.56749	.57142	.57535
0.2	.57926	.58317	.58706	.59095	.59483	.59871	.60257	.60642	.61026	.61409
0.3	.61791	.62172	.62552	.62930	.63307	.63683	.64058	.64431	.64803	.65173
0.4	.65542	.65910	.66276	.66640	.67003	.67364	.67724	.68082	.68439	.68793
0.5	.69146	.69497	.69847	.70194	.70540	.70884	.71226	.71566	.71904	.72240
0.6	.72575	.72907	.73237	.73565	.73891	.74215	.74537	.74857	.75175	.75490
0.7	.75804	.76115	.76424	.76730	.77035	.77337	.77637	.77935	.78230	.78524
0.8	.78814	.79103	.79389	.79673	.79955	.80234	.80511	.80785	.81057	.81327
0.9	.81594	.81859	.82121	.82381	.82639	.82894	.83147	.83398	.83646	.83891
1.0	.84134	.84375	.84614	.84849	.85083	.85314	.85543	.85769	.85993	.86214
1.1	.86433	.86650	.86864	.87076	.87286	.87493	.87698	.87900	.88100	.88298
1.2	.88493	.88686	.88877	.89065	.89251	.89435	.89617	.89796	.89973	.90147
1.3	.90320	.90490	.90658	.90824	.90988	.91149	.91309	.91466	.91621	.91774
1.4	.91924	.92073	.92220	.92364	.92507	.92647	.92785	.92922	.93056	.93189
1.5	.93319	.93448	.93574	.93699	.93822	.93943	.94062	.94179	.94295	.94408
1.6	.94520	.94630	.94738	.94845	.94950	.95053	.95154	.95254	.95352	.95449
1.7	.95543	.95637	.95728	.95818	.95907	.95994	.96080	.96164	.96246	.96327
1.8	.96407	.96485	.96562	.96638	.96712	.96784	.96856	.96926	.96995	.97062
1.9	.97128	.97193	.97257	.97320	.97381	.97441	.97500	.97558	.97615	.97670
2.0	.97725	.97778	.97831	.97882	.97932	.97982	.98030	.98077	.98124	.98169

Tab.2.1. *Normal distribution cumulative z-scores*

2.3. Demand Driven MRP (DDMRP)

In 2011, C. Ptak and C. Smith released the concept of *Demand Driven Material Requirement Planning* (DDMRP) for the first time as an appendix to the last published version of the Joseph Orlicky MRP seminal book "*MRP. The New Way of Life in Production and Inventory Management*", first released in 1975. In their review, the authors show the MRP inefficiencies created by trying to cope with modern VUCA supply-chains environments using an outdated set of assumptions. An important aspect of DDMRP is that it does not debunk all previous knowledge by introducing completely new concepts, as was done by Lean and Kanban. DDRMP instead aims *to fit the best of all inventory management and S&OP philosophies together nicely,* pursuing a real systemic-approach. In DDMRP, MRP is not considered "bad" but just "out-of-phase" with modern market dynamics, thus it still represents an insostituibile component of proper inventory management.

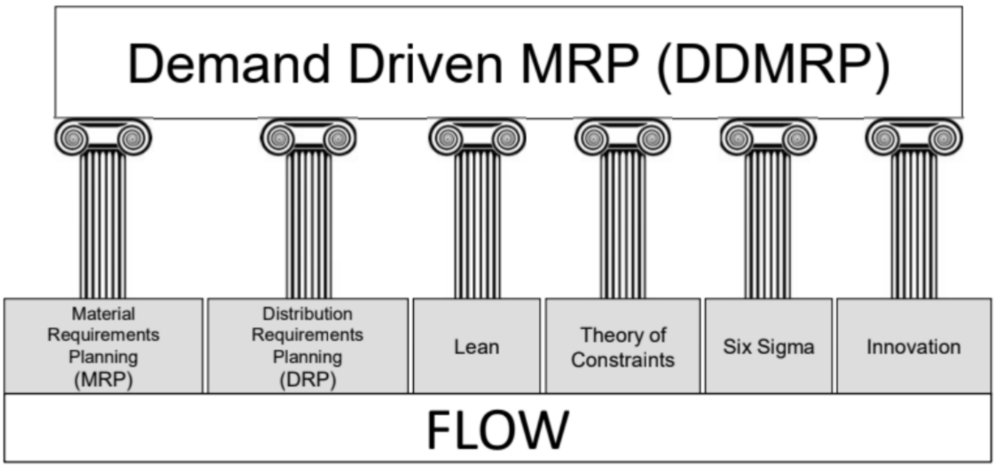


Fig. 2.5. *The six pillars of DDMRP sit on the command foundation concept of flow.*

The final aim of DDMRP is *maximising Return on Investment* (ROI) by *protecting the flow of relevant materials and information* through the concept of *strategic decoupling*, and putting *real materials consumption at the centre of the planning equation* introducing the concept of *Average Daily Usage* (ADU). To implement DDMRP, a five-steps general-purpose procedure is devised by the authors, as represented in Fig. 2. 6.

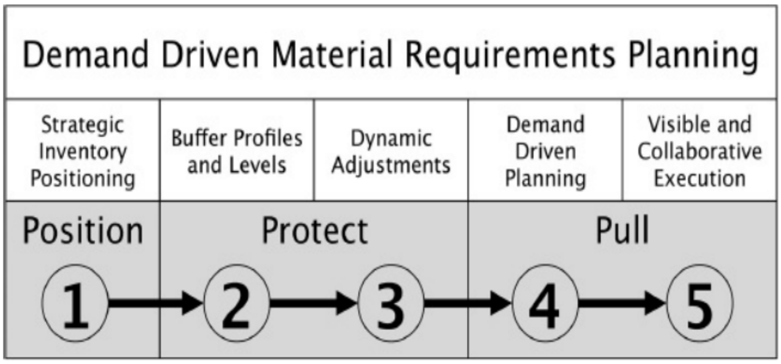


Fig. 2.6. *Implementation phases of DDMRP.*

All steps will be introduced in the following paragraphs, starting from why MRP fails in the modern context.

2.3.1. MRP in modern times

The advent of accessible computing during the 1950's allowed companies to outsource to computers one of the pivotal activities of most manufacturing environments: *Material Requirement Planning* (MRP). The APICS dictionary defines MRP as

a set of techniques that uses bill of material (BOM) data, inventory data, and the master production schedule to calculate synchronised requirements for materials. [...]

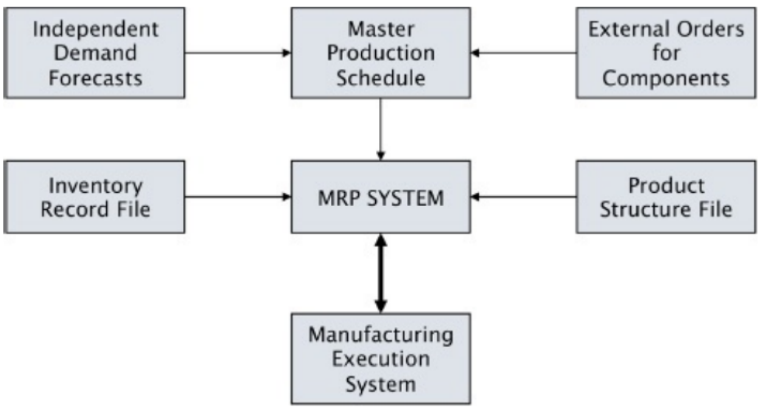


Fig. 2.7. *The MRP functional tree*

In other words, MRP carries the heavy-lifting task of *exploding the final product requirements down the product tree*, determining exactly when and how much of each component it is required so as to completely fulfil *planned* requirements, *netting reservoir stocks to zero.* Thus, the more sophisticated the product portfolio, the more valuable MRP is for a company. MRP represented a huge advancement for inventory management, allowing managers to fastly create a requirement schedule without being obliged to "keep something of everything" to offset the time required to perform the backtracking procedure manually. With time, the high adoption rate led MRP to be extended and embedded in what are known as, *Enterprise Resource Planning* (ERP), connecting materials management with capacity planning and financials. On the other hand, since its first development in 1950 by Joe Orlick and George Plossl, MRP underlying working assumptions were never re-tested against the ever-changing reality of supply-chain environments. The result is that nowadays MRPs are mostly known for their *delicate nervousness* rather than their utility. MRP nervousness, a very well-known issue to material planners, emerges from the fact that a deterministic exact procedure, such as MRP, is run against an imprecise, ever-changing input. As seen in Par. 1.2, companies mostly run on their forecasts to get ready for market. Thus, to produce the replenishment plan, activate material purchasing agreements, lay down the production schedule and generally plan-ahead, MRP is run upon such inputs. Then, when the real demand shows up, the MRP is re-run, completely changing its recommendations. It is not rare that upon MRP re-runs, materials that yesterday figured as excesses, today present shortages only recoverable by orders that should have been released days back. Such conditions strongly induce MRP's users to find *workarounds,* generally *distrusting* its effectiveness and letting MRP work under even less accurate information.

On the other hand, reviewing its initial conceptualisation. such MRP behaviour seems more a design feature than a flaw. Indeed, the basic MRP underlying assumptions, as introduced by Olircky is its seminal book are as follow

1. **Customer Tolerance Time is equal or greater than the Cumulative Manufacturing Lead Time.** This represents the less reality adherent assumption of MRP. In 1950 customers' expectations differ substantially from modern times. Ordering a new car model nowadays can mean for a manufacturer to only assemble customer customisations on top of a pre-assemble base model, pushing goods as fast as 2-weeks delivery for an item that in the past would have required substantially more, a market trend currently known as *mass-customisation*. As seen in Par. 1.3, modern customers are getting accustomed to overnight deliveries, obliging manufacturers to run MRP on always wrong forecasts so as to be able to complete the full purchasing and manufacturing cycle within CTT.

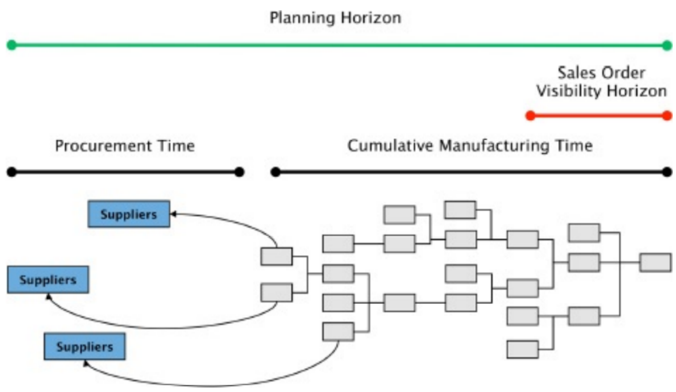


Fig. 2.8. *Relationship between Customer Tolerance Time and the Manufacturing Planning Horizon*

2. **Absolute precision of input data**. Thus, being inputs *cascaded* down the BOM, even slight schedule deviation from the initial MRP-run will not be manageable by the initial MRP plan. Being forecasts always wrong, such a condition is almost never met.
3. **No execution deviation occurs once the plan is generated.** Thus, the schedule is not resilient to any source of disruption, from simple but likely suppliers delivery delays (even small ones) to major contingent, but increasingly likely events due to supply-chains elongations, such as the Suez canal incident in 2021.

Following, the major effect produced by MRP nervousness is introduced.

2.3.2. Excess and Shortages

Any activity that transforms inputs into outputs can be defined as a *process*. Real processes are permeated by variability, either whether this comes from exogenous, inevitable and uncontrollable causes or as the sum of multiple endogenous causal effects acting on it. The first type of variability is called *natural*, denoted with σ_N, and is always manifested in any process. Processes subject only to natural variability are said to be *in statistical control*, meaning that all the measured values of the process outputs fall within $\pm\ 3\sigma_N$ of the process mean, μ_χ. As shown in the next chapter, if the outputs of the process affect the future values of its inputs, then the process can be defined as *dynamic* and be explained by differential equations. As seen in Par. 2., inventory can be seen as the output of a process of trying to satisfy an uncertain demand trend based on forecasts, which are essentially sophisticated bets over future consumption. At each timestep, the difference between what is forecasted and the real extracted demand value accumulates as *on-hand Inventory*. Is it then plausible to ask within which range inventory levels can be considered under (statistical) control. A rigorous approach would require studying the inventory natural distribution and estimating all its shape parameters thus quantifying its *natural tolerance range*. The *visible and collaborative* *execution component* of DDMRP tries to accomplish this task by observing two more practical basic facts instead.

As seen in Chapter 2, managers try to protect their productive assets from stock-outs by allocating safety stocks over the buffers based on desired service levels whereas the setting mechanism for maximum admissible inventory levels escalates in complexity with the frequency of the inventory review. Is thus plausible to believe that inventory fluctuates between these thresholds, hardly optimising total cost but at least keeping it controlled. Surprisingly, on a survey of 500 companies, C. Ptak and C. Smith observed that when considering all firm inventory, SKUs on-hand quantities usually tended to rather follow a *bimodal distribution* (Fig. 2.9) characterised by critical components in shortage and low-value materials in excess. Something they defined "too much of the wrong and too little of the right anytime, too much in total over time". Moreover, the authors observed an oscillation pattern of these parts moving between the two extremes after each new MRP re-run thus suggesting, as it will be introduced in Chapter 3, the presence of a possible underlying dynamic process governed by *goal-seeking feedback loops with delays.* (Sterman chapter. 4.1.3).

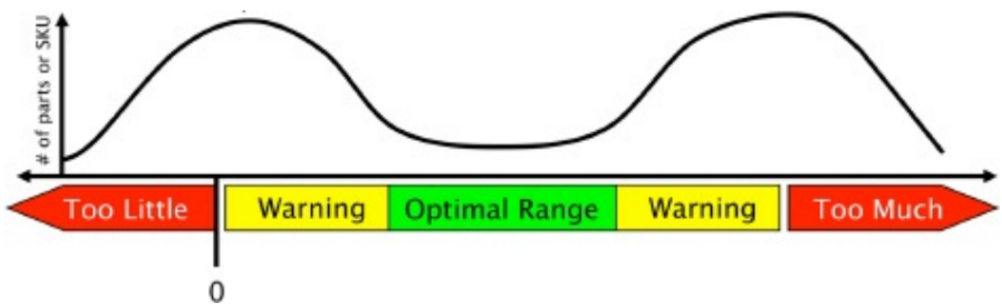


Fig. 2.9. *Ptak & Smith Bimodal inventory distribution*

A study from IHL Group in 2015 estimated that in the worldwide retail industry stock-outs weighted for \$634.1 B yearly in lost sales whereas the cost of overstocks accounted for \$471.9 B yearly. The cost of overstocks is easily grasped in the industry of disposable goods, such as food or drugs, where all unsold production is mostly incinerated. Both extreme positions thus generate the effect of a *loss*, operationally and financially. These losses can be modelled as proportional to the deviation from the value considered as the desired target, defining a *Loss Function* over the variability range. Conventionally, no loss is considered for values falling within the so-called *Customer Specification Range* (CSR), basically defining losses in a binary way. CSR is a common concept in manufacturing where clients define a *Lower Specification Limit* (LSL) and *Upper Specification Limit* (USL) between which they are willing to accept and buy the process output units. This is reasonable for values falling near the target but, as the process starts to deviate, the binary definition starts yielding doubting results where the client experiences sudden dissatisfaction after a slight marginal change in the output value. More sophisticated loss functions used in quality control are the *Taguchi Loss Functions* (TLF) which provide (Fig. 2.10) a more realistic view about losses generation, or customer dissatisfaction in general. TLFs allow any deviation to be penalised and "smoothly" explains the customer "satisfaction tipping point" reach. These concepts are utilised in Par. 2. to determine the optimal inventory levels suggested by DDMRP.

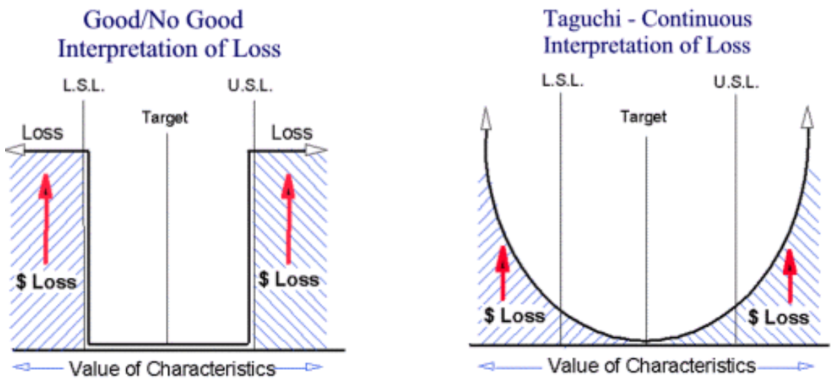


Fig.2.10. *Traditional loss functions compared to a symmetrical quadratic Taguchi loss function*

2.3.3. Strategic Buffer positioning and dimensioning

As seen in Par. 2.1, a common misbelief about proper SCM is *keeping inventories as low as possible* to minimise immobilised working capital. DDMRP steers to the opposite direction instead, by promoting the concept of *strategic decoupling*. Essentially, a *decoupling point* is represented by *physical material buffers*, placed in precise locations of the product BOM, that acts as a *variability absorber.* Decoupling points are the only places in BOM where DDMRP assumes guaranteed perpetual availability of components, as opposed to MRP where everything is considered *always available when needed.*

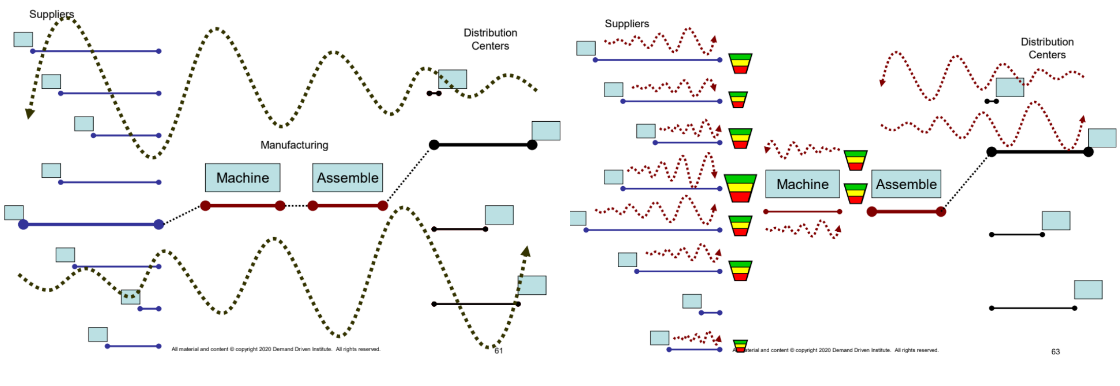


Fig. 2.11. *The effect of strategic decoupling on transmission of the bullwhip effect to the productive environment*

Thus, all activities between two decoupled positions can operate independently from the rest creating *independent sections* in the product BOM, as opposed to conventional MRP where everything is dependent. By doing so, DDMRP buffers assolve a second essential function: *lead-time compression*. Among the functions covered by buffers, one of them is *to buy time*. In typical DDMRP configurations, only two kinds of lead-times are considered

Manufacturing Lead-Times (MLT), is *the time it takes to manufacture the upstream part exclusive of lower-level lead times*. Thus, an assembled semis obtained by means of an assembling operation lasting 1 hour and requiring 2 components manufactured in respectively 2 and 4 hours, will have a MLT of 1 hour. MLT's underlying assumption is that *required child-components are available at parent order release date*; and

Cumulative Lead-Times (CLT), is *the longest sequence in the product structure defined in time*. Thus, in the previous assembled semis will have a CLT of 5 hours. CLT's underlying assumption is that *no child-components are available upon parente order release*.

When decoupling is instead considered, it is clear to see that said lead-times represent respectively the *upperbound* and *lowerbound* of the real lead-time value. Being buffered materials assumed always available by DDMRP, the upstream portion of the cumulative lead-time can be safely discarded, defining the pillar DDMRP concept of *Decoupled Lead Time* (DLT). Decoupled Lead Time is thus defined by their authors as

" *the longest cumulative coupled lead time chain in a manufactured item's product structure. It is a form of cumulative lead time but is limited and defined by the placement of decoupling points within a product structure.* "

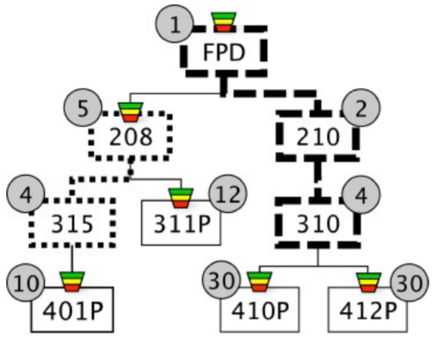


Fig. 2.12. *Lead-time compression in a simple BOM*

Fig. 2.12 visualises the lead-time compression applied by decoupling points, by allowing a lead-time reduction for the final-product FPD from 37 days to 7 days, while components 208 experience a reduction from 19 days to 9 days. Intuitively, the denser the buffer displacement in the BOM the lower the maximum DLT, which at the extreme a compression equal to the part MLT. On the other hand, such reduction comes at a cost which must be evaluated. Thus, a good DDMRP implementation *does not mean placing inventory everywhere*, but just where it is required to protect flow and maximise ROI.

The designation of the best spots in the BOM where to decouple is guided by an recursive generic *rule-based* procedure called "*strategic inventory positioning*", briefly introduced as follows. A buffer should be considered at a specific component location in the BOM if

1. *The CTT is shorter than the Cumulative Lead Time,*
2. *There are market opportunities coming from a faster Time-to-Market,*
3. *The forecasting horizon is considerably larger than the Sales Visibility Horizon,*
4. *The economic benefits outweigh the increase in working capital requirements.*

5. *The component is shared among multiple BOMs,*
6. *The considered part of the process is subject to high-variability from different sources.*
7. *A continuous flow is required to the downstream nodes.*

Being upper nodes in the BOM connected to many downstream ones, the iterative part of the procedure comes when evaluating alternative decoupling of all leaf nodes, raising a *combinatorial optimization problem* not exactly treated in the original DDMRP formulation.

To evaluate the economic positioning criteria and to be effective for their purpose, buffered positions must be sized appropriately to perform their claimed functions. This phase is called the "*strategic buffer dimensioning"* phase. In their original formulation, the authors discriminate between three component classes, namely "vanilla" *dynamic replenished parts*, *static replenished parts* and *min-max parts*. In this study, only the first kind are considered, being the other two just a subset of those. A typical DDMRP buffer is fully described by Fig. 2. 13.

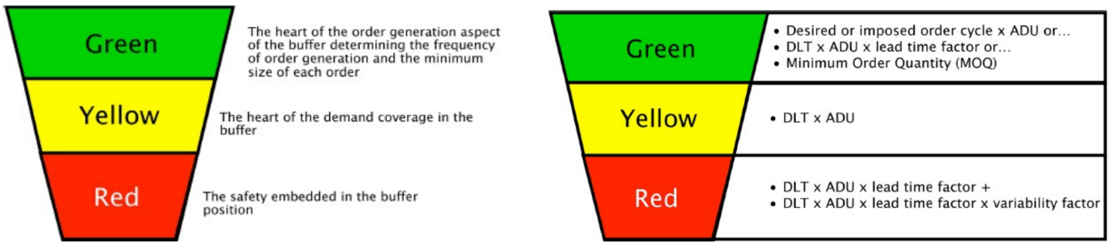


Fig. 2.13. *DDMRP decouple point structure for replenished parts*

The first thing that appears is the reutilisation of the redlight concept of Lean in the definition of the *buffer zones*. Buffer zones determine a decoupled position *response to external inputs* and *they do not equal to the total stocked inventory on hand*. In par. 1., the actual inventory on-hand is computed as a combination of the zones.

The **red zone** assolve the typical role of *safety stocks,* requesting higher materials on hand the higher the supply and demand variability are. Thus, such quantities must be really stored in the buffer location. Being accounting for two variability sources, the red zone is made out of two components

$$Red\ Base\ (i,\ t)\ =\ RB(i,t)\ =\ Lead\ Time\ Factor\ (i,t)\ *\ DLT\ (i,t)\ *\ Average\ Daily\ Usage\ (i,t)$$
$$Red\ Safety\ (i,\ t)\ =\ RS(i,t)\ =\ RB(i,t)\ *\ Demand\ Variability\ Factor\ (i,t)$$
$$Red\ Zone(i,\ t)\ =\ RZ(i,t)\ =\ RB(i,t)\ +\ RS(i,t)\ =\ RB(1\ +\ DVF)$$

where i is the i-th element in the BOM and t is time.;

The **yellow zone** assolve the role of the *cycle stock,* thus covering demand during lead time. Being DLT the most accurate metric for lead-time in DDMRP, the yellow zone is determined as

$$Yellow\ Zone(i,\ t)\ =\ YZ(i,t)\ =\ Average\ Daily\ Usage\ (i,\ t)\ *\ Decoupled\ Lead\ Time\ (i,t)$$

Being partially consumed, it can be proved that only half of the yellow zone is stationary in the buffer location.

The **green zone** determines the *minimum order size* released by a DDMRP system.

$$GZ(i,t) = MAX\{\, Yellow\ Zone(i,t) * LTF(i,t)\ ,\ Desired\ Order\ Cycle\ *\ ADU(i,t)\ ,\ MOQ(i,t)\,\}$$

where MOQ(i,t) represents the *Minimum Order Quantity for the i-th part in the BOM*, whereas the Desired Order Cycle represents the planners' desired average number of days elapsed between two issued orders. At this point the similarities of DDMRP with traditional *continuously reviewed (R,Q) inventory policies,* introduced in Par. 1.2, are evident, confirming the DDMRP pursuit of integrating together what it is already known to work properly.

To perform the buffer zones computation, the values of ADU, DLT, DVF and LTF must be computed. The most important parameter is the ADU given that all zones depend on it. Indeed, the ADU stands within the key innovation brought by DDMRP in the MRP context, shifting the planning focus on real consumptions. On the other hand, being DDMRP an inclusive-oriented methodology, forecasts are not totally discarded but whether to use it or not in the ADU estimation process is a decision left open to the implementing user. For the determination of ADU three key decisions must be taken

1. **The time-position of the ADU reviewing window**, deciding whether to only use past consumption data, forecasts or *blend the two approaches.* The blended approach seems to be the desirable trade-off between proper adherence to real consumptions and visibility of short-termed expectations about future consumption. In case of non-availability of past data (e.g. new product introductions) further investigation is required to extrapolate a *trusted* ADU trend to accommodate the lack of data (e.g during production ramp-ups phases);

2. **The size of the ADU reviewing window**, thus deciding the *smoothing factor* of the ADU estimate. Small window sizes might make ADU suffer from the same MRP nervousness.

3. **The updating frequency of the estimate,** thus deciding the *computational effort* of running DDMRP. On the other hand, being computational power not really a constraint for many applications nowadays, *daily updating of ADU estimates yields the most accurate DDMRP response*. Being virtually updated on a daily basis, ADU represents the most *dynamic part of DDMRP*, letting buffer zones change based on real consumptions. Chap. 2 introduces the Whirlpool DDMRP implementation case study where massive integration efforts made by Whirlpool IT department led the ADU to be updated on a daily-basis.

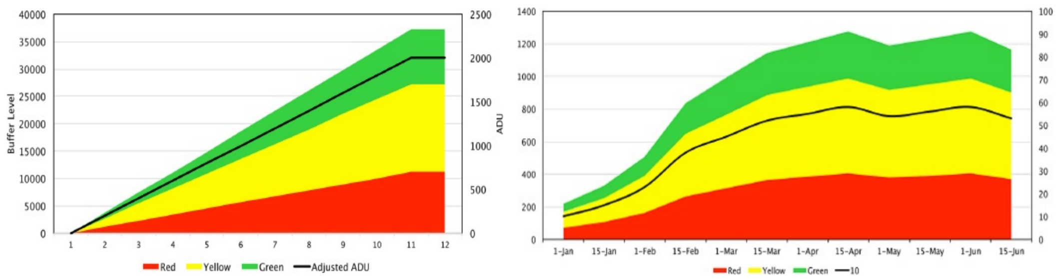


Fig.2.14. *ADU impact on buffer zones under different working conditions (market introduction and demand increase)*

For what concerns DVF and LTF, an initial distinction between *purchased items* and *manufactured items* is done. Then, a rather simplistic rule based on the *pareto approach* is indicated by the authors. For LFT, an analysis of DLT distribution of the whole BOM is required, to then classify *buy items* (BI) as

1. *Short lead-time* (S), those building approximately up to 30% of the DLT distribution
2. *Medium lead-time* (M), those building approximately from 31% to 70% of the DLT distribution
3. *Long lead-time* (L), the remaining items

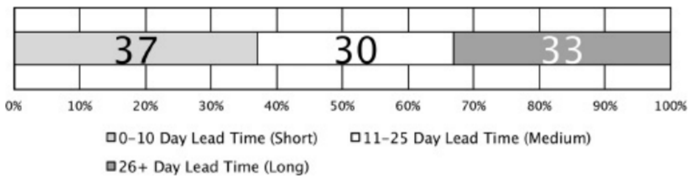


Fig. 2.15. *Example of determination of LTF for purchased items*

whereas, *make items* (MI) as

1. *Short lead-time* (S), those building approximately up to 60% of the DLT distribution
2. *Medium lead-time* (M), those building approximately from 61% to 85% of the DLT distribution
3. *Long lead-time* (L), the remaining items

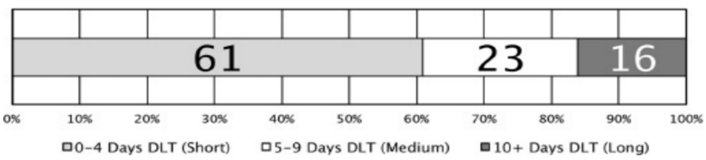


Fig. 2.16. *Example of determination of LTF for purchased items*

For both item categories, LFT can be set accordingly to the pertaining item macroarea as suggested in Tab. 2.2. The definition of the proper LFT in the range is left available to the final implementing user.

Lead Time Class	Lead Time Factor
Short Lead Time	0.61 - 1
Medium Lead Time	0.41 - 0.6
Long Lead Time	0.2 - 0.4

Tab. 2.2. *Available Lead Time factors*

It is worth noticing the inverse relationship between Lead-time length and LFT. Finally, for what regards DVF, the analysis is simpler and dictated only by the *frequency of spikes in its customer demand*, defining

1. *Stable items* (SV), the ones presenting no order spikes in the sales records;
2. *Medium variable items* (MV), the ones presenting occasional order spikes in the sales records;
3. *Highly variable items* (HV), the ones presenting frequent spikes in the sales records;

Deciding when a spike occurred is left open to the final implementing users. DVF can be set accordingly to the pertaining item macroarea as suggested in Tab. 2. 3.

Variability Class	Demand Variability Factor
Short Lead Time	0 - 0.4
Medium Lead Time	0.41 - 0.6
Long Lead Time	0.61 - 1

Tab. 2.3. *Available Demand variability factors*

It is worth noticing the direct relationship between Lead-time length and DVF. Thus, by combining all SKUs characteristics, 18 basic SKUs profiles are possible. (e.g. (BI, S, MV) or (MI, M, HV)). Moreover, the DVF and LTF contribution to safety stock can be summarised in a unique z_{eq} *factor* given that

$$RZ = RB(1 + DVF) = ADU * DLT * LTF * (1 + DVF) = YZ * z_{eq}$$
$$z_{eq} \in [0.2,\ 2]$$

reinforcing the parallel drawn with *(R, Q)* policies.

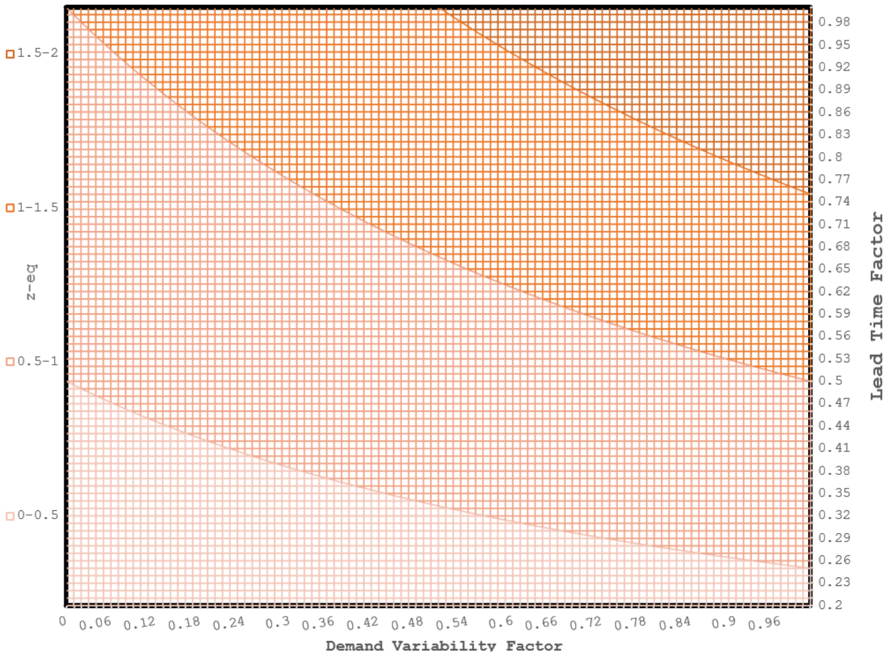


Fig.5.17. *Variability range of DDMRP* z_{eq} *factor as a function of LTF and DVF*

Finally, the buffer dimensioning phase is marked as completed by summarising all buffer zones together so to determine the *buffer thresholds*

$$Top\ of\ Red\ (i,t) = TOR(i,t) = RZ(i,t)$$
$$Top\ of\ Yellow\ (i,t) = TOY(i,t) = TOR(i,t) + YZ(i,t)$$
$$Top\ of\ Green(i,t) = TOG(i,t) = TOY(i,t) + GZ(i,t)$$

and release of the *buffer profile*, as shown in Fig. 2.18.

Example Part Buffer Calculation

Average Daily Usage	10	Green Zone	70
Buffer Profile	M, M (.33), L (.33)		LT Factor: 60 (DLT (12)x ADU (10) x Lead Time Factor (.5))
MOQ	50		Minimum Order Quantity: 50
Imposed or Desired Order Cycle (DOC)	7 days		Order Cycle: 70 (7(OC) x 10(ADU))
Decoupled Lead Time (DLT)	12 days	Yellow Zone	120 (12(DLT) x 10(ADU))
		Red Zone	80 (Red Base (60) + Red Safety (20))
			Red Base: 60 (DLT (12)x ADU (10) x Lead Time Factor (.5))
			Red Safety: 20 (Red Base (60) x Variability Factor (.5))

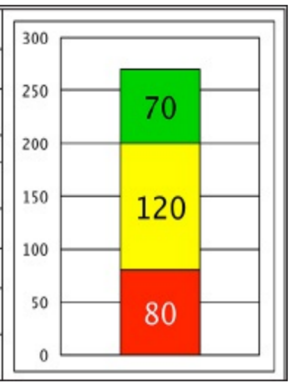


Fig.2.18. *The buffer profile generated as a result of the strategic buffer dimensioning phase*

With buffer profiles computed for all possible decoupling alternatives, it is possible to conclude also the strategic buffer positioning phase by comparing the economic positioning criteria of each position to each other, as shown in Fig. 2.19, so as to fix the final decoupled positions in the BOM.

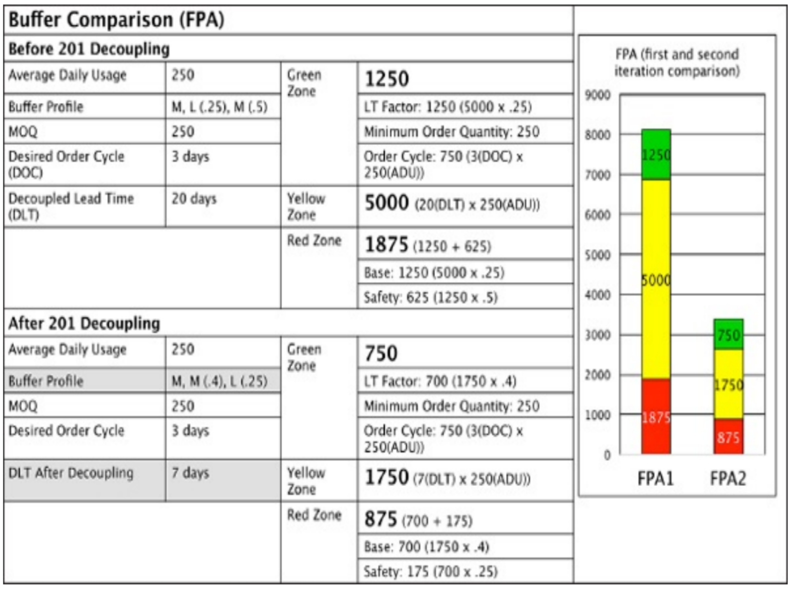


Fig. 2.19. *Benchmarking economic benefits extracted from different decoupled BOM configurations*

2.3.4. Demand Driven Planning

Once buffered positions are known and properly dimensioned, all the conditions are set to run DDMRP and let buffers execute their last essential function: *replenishment order generation*. Because buffered positions are the equivalent of independent leaf nodes in MRP, starting from them it must be possible to generate an exact dependent requirement schedule for all downstream components. This task is performed by means of the *Net Flow Equation* (NFE) and the concept of *decoupled explosion*.

The Net Flow Equation is the planning heart of DDMRP and, as anticipated in Par. 2.2.3, resembles the same reordering equations of a *continuously reviewed (R,Q) inventory policy*. NFE is defined as

$$Net\,Flow\,Position(i,\ t) \ = \ On\,Hand\ (i,\ t)\ +\ Open\,Supply\ (i,t)\ -\ Qualified\,Sales(i,t)$$

Looking closely, the first two terms are nothing more than the Inventory Position seen in Par. 2. . whereas

1. **Qualified Sales** are defined as t*he sum of sales orders past due, verified sales orders due today, and qualified spikes.*

$$Qualified\,Sales(i,t) \;=\; Daily\,Due\,Orders\;(i,t)\;+\;Qualified\,Order\,Spikes(i,t)$$

2. *The time horizon within which qualified sales are considered visible* is called **Demand Visibility Horizon** (DVH) and only allocated sales orders happening within it will be considered in the qualified demand computation.

3. **Qualified Order Spikes** (QOS) are instead defined as *a future qualifying quantity of known cumulative daily demand, included in the demand visibility horizon, that threatens the integrity of the buffer by overshooting the demand spike threshold.*

4. The **Demand Spike Threshold** (DST) is an arbitrarily set amount of daily demand that is considered by the final implementing user as threatening the buffer ability to absorb variability. In other words, discarding the presence of the peak will eventually lead to stock-outs. DDMRP authors provide different possible heuristics to set DST but complete freedom is left to the final implementing user. A typically applied rule is to consider qualified spikes all quantities depleting more than half of the safety stocks.

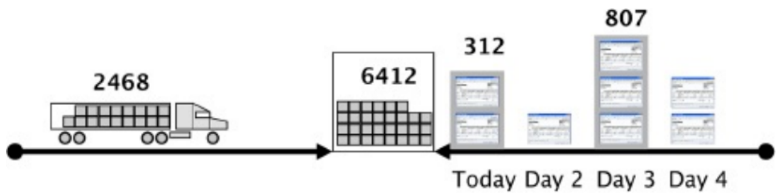


Fig. 2.20. *Visual representation of the NFE*

Thus, to put it in another words, NFE answers the following basic planning questions

1. *How much is available to satisfy daily demand?* **On-Hand quantities;**

2. *How much will be received in the next few days?* **On-Order quantities;**

3. *What is the urgent demand?* **All backorder and daily due orders;**

4. *What part of future sales orders might cause problems?* **Qualified order spikes.**

Once defined the DVH and OST , *replenishment orders* are issued so as to *re-establish the Net Flow Position to the Top-of-Green* (TOG) *when that overshoot Top-of-Yellow* (TOY) ***in every decoupled position***. Thus, the TOG is the *desired net flow position* in DDMRP and defines the max inventory level of a traditional continuously reviewed (R, Q) policy, while the TOY represents the *reorder point*.

$$Reorder\ Point \;=\; R_{DDMRP} = TOY(i,t) \;=\; RZ(i,t) \;+\; YZ(i,t) \;+\; GZ(i,t)\,;$$

$$Replenishment\ Order \;=Q_{DDMRP} = \begin{cases} TOG \;-\; NFP & if\ NFP \;<TOY\,; \\ 0 & otherwise\,; \end{cases}$$

The key innovation of DDMRP in this regard is that it basically implements a *dynamically adjusted continuously reviewed (R, Q) inventory policy*. Indeed, the dynamic part of the rule is provided by the order spike detection logic embedded in the NFP. Thus, in absence of sudden lumpy batch qualified orders, DDMRP will behave as in a classic (R,Q) policy, where Q_{DDMRP} = TOY - OH - OS + QD, whereas in presence of a spike Q_{DDMRP} > Q during the entire length of the demand visibility horizon.

The generated replenishment order Q_{DDMRP} is presented to the material planner as a *recommendation*, as done byMRP, which must be approved or rejected. Upon acceptance, the said order is scheduled as due after a DLT unit in the future and *the net flow equation is increased by its quantity* given that On-order quantities have now increased. To guide the phase of *demand driven planning*, DDMRP fully exploits such reordering mechanism to also determine the *planning orders priorities*, defined as the percentage of penetration of the NFP in the TOG. Thus, orders issued when the NFP penetrated the YZ will be prompted with a yellow flag, raising a medium-to-low level of concern, whereas more harsh NFP penetrations down to the RZ will appear more urgent.

Today's Date: 15-July

Part#	Planning Priority	On-Hand	On-Order	Qualified Demand	Net Flow Position	Order Recommendation	Request Date	Top RED	Top YELLOW	Top GREEN	Lead Time
406P	RED 19.8%	401	506	263	644	2606	4-Aug	750	2750	3250	20
403P	YELLOW 43.4%	1412	981	412	1981	2579	23-Jul	1200	3600	4560	8
402P	YELLOW 69.0%	601	753	112	1242	558	24-Jul	540	1440	1800	9
405P	YELLOW 74.0%	3400	4251	581	7070	2486	24-Jul	1756	7606	9556	9
401P	YELLOW 75.1%	2652	6233	712	8173	2715	25-Jul	2438	8938	10888	10
404P	GREEN 97.6%	1951	1560	291	3220	0		1050	2550	3300	6

Fig.2.21 *Planned order prioritisation mechanism of DDMRP*

A final remark is necessary regarding the *decoupled explosion* performed by DDMRP. Whereas in MRP only the leaf node's demand is considered independent and qualified to be cascaded on the whole BOM, generating nervousness, in DDMRP the replenishment mechanism seen above is triggered *everyday at each decoupled position*. Thus, in case a buffered position issues a certain replenishment order, such order is transmitted to the first subsequent downstream buffered position which receives such an order as part of its *qualified demand*. Only in the case where also the NFP of the downstream buffered position results below its TOY threshold, an additional replenishment order will be transmitted to the deeper levels of the BOM. This concept prevents DDMRP from creating nervousness throughout the BOM schedule, allowing it to be safely rerun on a daily basis. Moreover, the concept of *decoupled explosion* represents a clear integration of a Kanban-based "pull logic" to the typical MRP "push logic", thus bringing together methodologies that were usually considered at the end of the same spectrum.

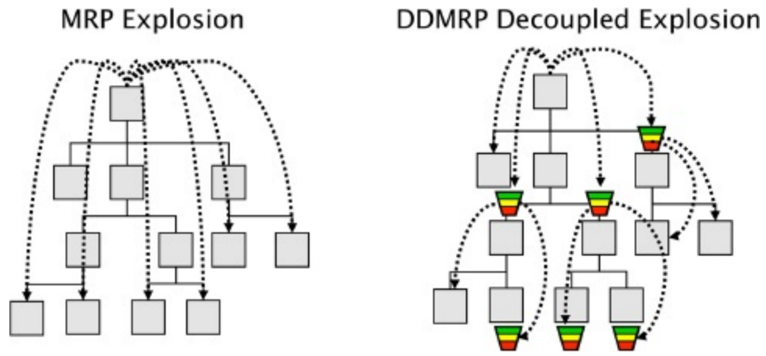


Fig. 2.22. *DDMRP Decoupled explosion of dependent requirements versus MRP explosion*

2.3.5. Demand Driven Execution

During the planning phase the replenishment orders are generated against the status of net inventory position through the NFE and scheduled so as to always keep it above TOY. From that moment on, the focus shifts on the real inventory on-hand levels, entering the final *execution phase* of DDMRP. In the execution phase, the NFE is put aside and the open supply orders' promised delivery dates are monitored against the *average inventory on-hand* in the buffered position so as to decide whether an order must be *expedited* or not to protect the buffer integrity. The buffer zones are thus rearranged so as to serve the execution task, as shown in Fig. 2.23, by exploiting the TLFs concepts seen in Par. 2.2.2 to determine a *desirable inventory variability range*. This range will be such that the costs from deviation toward shortages and excess are contained.

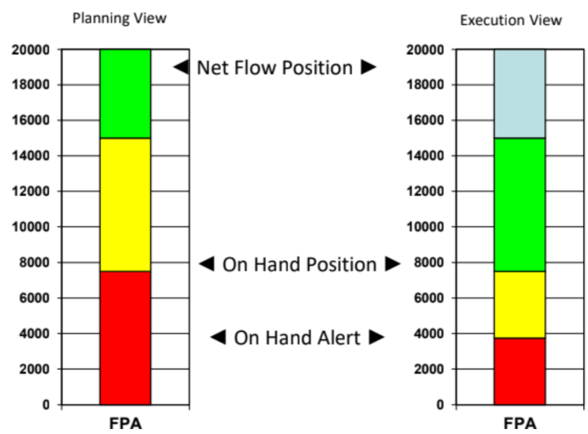


Fig. 2.23. *Planning view versus execution view of DDMRP buffered positions*

While stock-outs easily identify the lowerbound to the variability range of inventory, for each *i*-th SKU DDMRP defines the upper-bound as a combination of the buffer zones, as follows

$$\text{On-hand Inventory}(i, t) \in [\, LB=0,\ UB=TOR(i, t) + YZ(i, t)\,]$$

Then, being the cycle stock periodically replenished by orders released via the NFE which are constrained to be at least as big as the GZ, the lower and upper specification limits can then be imposed over the initial variability range defining the

$$\text{Optimal On-hand Inventory } (i, t) \in [\, LSL = TOR(i, t),\ USL = TOR(i, t) + GZ(i, t)\,]$$

Thus, this is equivalent to saying that, at-regime conditions, the *healthy* inventory status is determined by a situation where only the cycle inventory is used to feed downstream nodes, never contingently disposing of safety stocks nor accumulating excesses, releasing a replenishment order always as large as the GZ which is never affected by delivery delays. Finally, the above optimal inventory range implies a *desired optimal on-hand inventory level* of

$$E(\text{Optimal Inventory Level})\ (i, t) = (\, LSL + USL\,)/2 = TOR(i, t) + (½)^*GZ(i, t)y$$

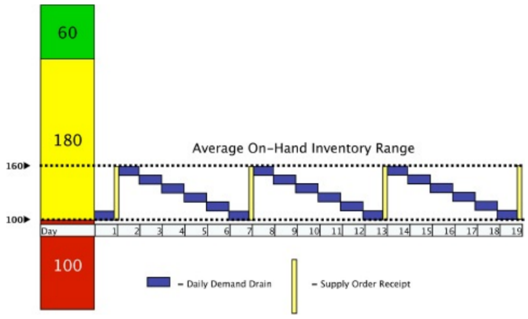


Fig.2.24. *Visual proof of actual inventory on-hand available in the buffered position*

This proves what was said in Par. 2.2.3 regarding the actual on-hand quantities kept in the buffered position and it implies requiring a *desired inventory coverage* of

$$E(\text{Inventory Coverage})(i, t) = (TOR(i, t) + (½)^*GZ(i, t)) / ADU(t)$$

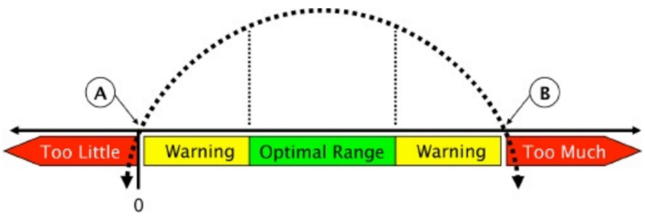


Fig. 2.25. *The optimal variability range of on-hand inventory determined exploiting Taguchi Loss Functions*

As for the planning phase, DDMRP exploits the above mechanics to provide the user with effective warning *on-hand alerts* based on the *penetration of actual on-hand inventory into the safety stocks*. The higher the penetration, the higher the alerting level being the real on-hand approaching a stock-out situation.

A final observation leads to say that the formulations above resemble the one presented for continuously reviewed *min-max (s, S)* inventory policy, that is the average inventory level produced by DDMRP is equal to safety stocks plus half the average order size. The major difference between the two lies in the safety stock formulation where the *safety factor z* is not used in DDMRP, effectively excluding the "*service level goal*" logic from the model. While the conventional normality assumptions underlying the safety factor are indeed questionable (C.E. Clark et al), on the other hand, DDMRP leaves to the planner an even higher degree of freedom, segmenting the domain of LFT and DVF into generic "short/medium/long" and "low/medium/high" categories respectively for lead time length and demand variability. This observation is detailed in C.J. Lee et al where is shown how a planner facing a DLT of 5 days (short category) and ADU of 1000 pcs can set (LFT, DVF) in such a way the total maximum safety stock attainable peaks to 10.000 pcs while the minimum is only 3600 pcs, a variability range of almost three times that make DDMRP final performances questionable.

				F_V					
				Low		Medium		High	
				Min	Max	Min	Max	Min	Max
Lead time		F_L		0.20	0.40	0.41	0.60	0.61	1.00
Long	35	Min	0.20	8,400		9,870		11,270	
		Max	0.40		19,600		22,400		28,000
Medium	20	Min	0.41	9,840		11,562		13,202	
		Max	0.60		16,800		19,200		24,000
Short	5	Min	0.61	3,660		4,301		4,911	
		Max	1.00		7,000		8,000		10,000

*Empty cells indicate irrelevant combinations.

Tab. 2.4. *Exaggerated safety stock variability generated by the DDMRP guidelines, extracted from C.J. Lee et al*

Chapter 3

Problem Setting and Research Questions

*"I **know** that I know **nothing**. "*
cit. Socrate

In this chapter the research questions of this study are derived from a system literature review carried against state-of-art academic literature about DDMRP. Finally, the Whirlpool case study used to validate the author hypothesis is detaily illustrated, where the 6-month internship period at the company let the author participate in the pilot DDMRP implementation at the Cassinetta plant.

3.1. Open issues emerging from current DDMRP literature

Having discussed the general scenario of Supply Chains within which DDMRP is embedded and once reviewed the viewpoint of its creators, it is now crucial to understand what is the academic position about it and whether there is evidence of the DDMRP claimed benefits.

To do that, a simple systematic literature review (B. Kitchenham 2004, M. N. Saunders 2019) has been performed against only peer-reviewed papers collected on the online directory *Scopus* (www.scopus.com). As of the time of writing, the launched query :

```
TITLE-ABS-KEY ( "ddmrp" OR "DDMRP" OR "Demand Driven MRP" OR
"demand driven MRP" OR "demand driven mrp" OR "demand driven
material requirements planning" OR "Demand Driven Material
Requirements Planning" )
```

anchored only 35 documents, ranging from 2007 to 2022, covering the fields of Engineering (33% of the documents), Business, Management & Accounting (24% of the documents), Decisional Sciences (18% of the documents), Computer Science, Mathematics, Physics, Economics and others (remaining 25%). Only 2 papers (Azzamouri A. 2021, Orue A. 2020) performed systematic literature reviews, respectively collecting and reviewing 57 (Azzamouri et al, 2021) and 16 (Orue et al, 2020) documents retrieved from different providers such as Web of Science, EBSCO, Google Scholar and Scopus.

While the small corpus of documents retrieved might suggest an error in the query launched, a quick read of Azzamouri A. 2021 confirmed the result that even if first released more than 10 years ago, the DDMRP methodology has still not reached a significant publication level in the scientific literature (Azzamouri A. 2021) compared to alternative methods. In addition to this first finding, the main open issues are summarised below merging Azzamouri et al, 2021 and Orue et al, 2020 findings with the extracted corpus of documents.

1. **Practitioners' claims about "revolutionary DDMRP performances" are supported by limited public data.** Even if the Demand Driven Institute fiercely provides an extensive collection of successful cases of DDMRP implementations (www.demanddriveninstitute.com/case-studies), detailed data quantifying the actual benefits gained and cost incurred are difficult to find. This is directly seen in literature where most of the case-study-based works are done using pedagogical simulated datasets rather than real industrial applications (Azzamouri et al, 2021). Moreover, implementing managers have incentives to report inflated figures to justify the major organisational overhaul efforts required by DDMRP.

2. **Only a few industrial sectors are well documented.** In particular, DDMRP implementations in the automotive and ink production sector are well documented in Shofa & Widyarto, 2017, Kortabarria & Elizburu, 2018 and Ihme & Stratton, 2015. Applications in other fields are only summarised in Bahu et al., 2019, and Bahu et al., 2018.

3. **Most of the research is focused on performance analysis and benchmarking.** Only a fraction of papers debate the validity of the DDMRP foundations and propose new approaches.

4. **Is therefore unclear what are the Key Success and Failure Factors of DDMRP implementation.** A debatable point is indeed present over the "subjectivity trait" of DDMRP where planners are required to set demand and supply variability factors to deduct the buffer R/Y/G thresholds. These in turn change the operative setup of DDMRP, thus its final performances. For instance, planners may exploit the fact that all forecasts are wrong and questionable (D. Simchi-Levi, *Chap.2*) to set very high demand variability factors to increase the average inventory position of the SKUs they manage so as to reduce the chances of stocking out and lower service levels attributable to them. An executive manager interested only in reported service levels might attribute these benefits to DDMRP "super-powers" when that is only due to a higher total on-hand inventory coverage. This subjectivity trait of DDMRP is questioned in C. J. Lee et al and an unbiased formulation for dimensioning DDMRP Safety Stocks (TOR) is proposed.

5. **Is unclear whether DDMRP is a generalizable procedure.** Only Al-Ammar, 2018, documented the implementation of a hybrid DDMRP-Kanban approach, suggesting a "domain of applicability" of DDMRP over Kanban. Most of the studies try instead to declare a winner between DDMRP and other inventory management policies. The same

DDMRP authors in their seminal book included a case study regarding the DDMRP implementation in the clothing retailing industry. In such contexts the number of SKUs managed by a single company is so high as to let individual ADUs fall near-zero. Moreover, in retailing inventory must also address the "retailing function", thus a minimum amount of it must be always used to display merchandise to the customer. Hence, SKUs are effectively used but not always there are direct sales attached to their consumption. As reported by the implementing manager "*these circumstances made it impossible to apply the conventional techniques suggested by DDMRP for buffer sizing*" given that with that low ADUs both RZ and YZ would be set to 0, disengaging DDMRP from its initial goal of managing inventory.

6. **Is unclear how DDMRP performs in complex environments or under extremely stressful conditions**. Most of the studies deal with simple productive environments like flow-shops manufacturing products with simple BOMs. This is reasonable considering the DDMRP literature is still trying to validate the base model and given that it is very well known from Operational Research literature how fastly a problem can escalate in solving complexity even when only two different machines working on the same job schedule are considered.

7. **Poor to no attention on Demand-Driven Planning and Execution DDMRP components.** "AS-IS" DDMRP uses the Net Flow Equation to generate supply orders relying on an infinite downstream capacity assumption. To the author's knowledge, only Dessevre et al, 2019, considered capacitated systems.

8. **Strategic Demand Driven S&OP is unexplored.** Only one article proposed an implementation of a rule-based system to guide S&OP processes toward building the fully "Demand-Driven Enterprise".

9. **Major focus on productive environments rather than distribution.** C. Ptak and C. Smith provide an extensive look in <*citation to DDMRP book here*> on how DDMRP logic can easily be extended to the distribution network planning theme. In literature, only one paper (Erraoui et al., 2019) tried to do it.

10. **System Dynamics has never been used to explore DDMRP.** Extensive use of Discrete Event Simulation is done instead, followed by implementations of Genetic Algorithms and rule-based systems. In turn, apart from Dessevre et al., 2019, where lead time variability is considered and dynamically managed, no other papers deal with the parameters' dynamic adjustment according to the system's state (Azzamouri et al., 2021). Moreover, **there is no evidence of exact solving methods for any DDMRP component.**

3.2. Research questions

Considered all the above, this study aims at answering the following research questions:

RQ1. *How well does the DDMRP perform with respect to traditional inventory min-max policies in terms of Service Level, Inventory Turnover and average WIP inventory for different ABC-XYZ product demand profiles?*

RQ2. *How sensible are the DDMRP performances to the arbitrarily set LFT and DVF parameters?*

RQ3. *Does the DDMRP order release logic "stress the system" in presence of internal or external capacity constraints?*

RQ4. *Does DDMRP reduce excess generation during periods of high demand variability generated by unforecastable events like global pandemics and sudden global supply shortages?*

RQ5. *How much does the Order Spike Visibility feature of DDMRP drive final performances?*

RQ6. *Is System Dynamics flexible enough to be embedded in current S&OP processes?*

This is done by analysing the industrial case study of the Whirlpool EMEA inventory overshoot occurred at the Cassinetta (IT) plant during the unprecedented era of supply-chain disruption led by the COVID-19 pandemic, Suez Canal accident in 2021 and the on-going Ukrainian War conflict. The *uniqueness of the study* is given by the **development of a first-of-a-kind** (to the author knowledge) **System Dynamic model of DDMRP**, aimed at studying its performance in non-traditional settings and evaluating whether the excess generation in Cassinetta might have been prevented through its adoption. In this way, an example of the possible "what-if" use of System Dynamics in S&OP processes is shown. Moreover, such use-case of SD provides evidence of its applicability also in more operative environments, typically dominated by DES. Finally, the study sheds light on DDMRP implementation in the not yet documented sector of "white goods" and home appliances.

3.3. A Case Study : Excesses and Shortages in Whirlpool EMEA

Whirlpool Corporation is an American global leading manufacturer and distributor of laundry and kitchen appliances, also called *white goods*, headquartered in Benton Charter Township. Michigan (US). Globally, Whirlpool Corporation counts over 7000 suppliers, 30.000 trade partners and 70 manufacturing and R&D centres.

3.3.1. Whirlpool Supply-Chain

Whirlpool EMEA S.p.A. (Whirlpool) is the EMEA (Europe, Middle-East & Africa) operating segment of Whirlpool Corporation, headquartered in Pero (IT). Born after the acquisition of the Italian Indesit Company SpA brand in 2014 and the later merger in 2016 of Whirlpool Europe S.r.l. into it, Whirlpool EMEA S.p.A. has a sales presence in 35 markets and 11 manufacturing and technology research centres in 5 countries (Fig. 3.1), positioning as the largest player in the region, with its three pan-European brands, Whirlpool, Indesit and KitchenAid, two regional brands, Hotpoint and Bauknecht, and a number of other local brands, including Scholtes, Ariston, Laden, Polar and Ignis (Fig. 3.2), shipping around 25 MLN products yearly. The product lines are grouped into 5 main categories, ordered by 2021 direct profit margin: *Laundry, Cooking, Refrigeration, Dishwashing, IBU & Others*; with most of the sales concentrated in the *Northern Europe, France, Italy* and *Russia* subclusters.

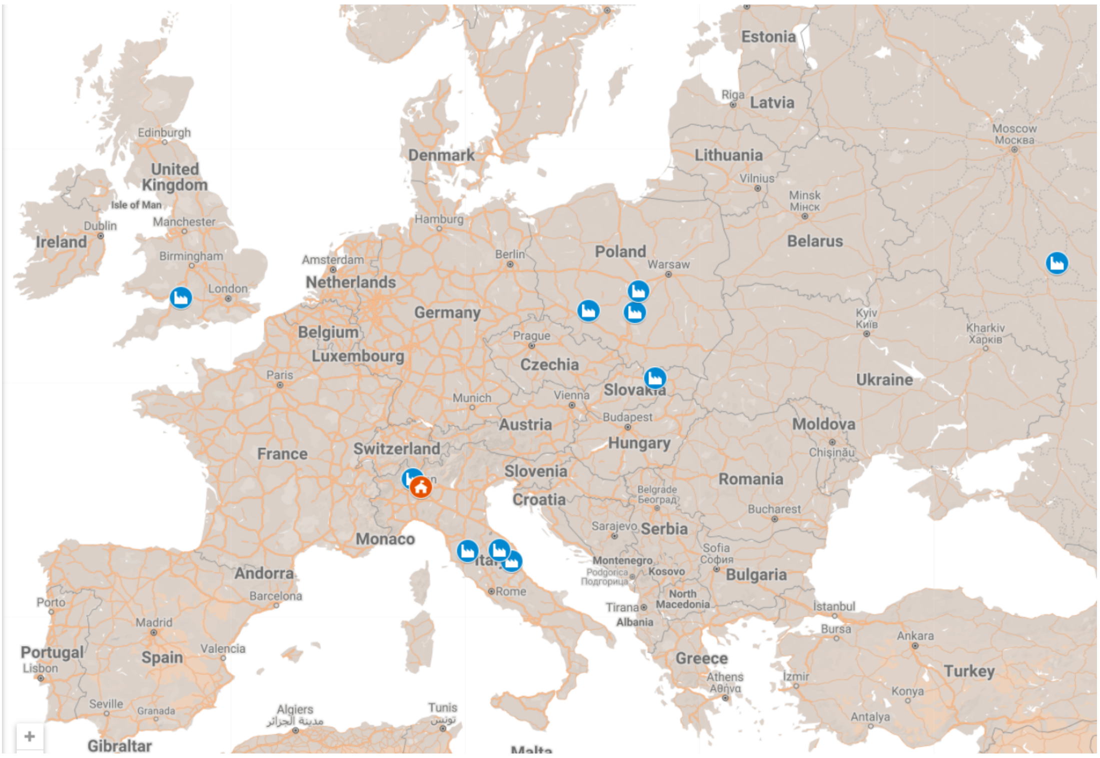


Fig.3.1. *Whirlpool factories location in EMEA*

Fig.3.2. *The Whirlpool Brands*

Factory location	**Product category**	**Productive volumes** (units / year)
Cassinetta di Biandronno (IT)	Cooking, Refrigeration	> 2 MLN
Comunanza (IT)	Laundry	> 660.000
Melano (IT)	Cooking	> 1.9 MLN
Siena (IT)	Refrigeration	> 200.000
Łódź (PL)	Cooking, Laundry	> 860.000
Radomsko (PL)	Dishwashing	> 2.7 MLN
Wrocław (PL)	Refrigeration	> 1.3 MLN
Lipetsk (RU)	Laundry, Refrigeration	> 3.3 MLN
Poprad (SL)	Laundry	> 700.00
Yate (UK)	Laundry	> 180.000

Tab.3.1. *Whirlpool factories production type and yearly volumes*

While most of the business functions (Finance, Strategic Planning, Integrated Supply Chain, Executive Management) are located in Pero (MI), the Procurement Office is still located in Cassinetta di Biandronno (VA) alongside its historical plant. The plant, divided into three main production areas (Fig. 3.3), plays a pivotal role in the production of built-in ovens, microwaves and refrigerators, releasing more than 2 million units yearly. In addition to its productive functions, the plant serves as an important field for the R&D of products and best practices.

To source its plants Whirlpool built over the years a global supply-base of 781 vendors, distributed mainly in Europe and Asia, totalizing a cumulative spend of 2.8B EUR (Fig.3.4). From a purchasing perspective, all items (make/buy) are categorised into 3 main classes, namely *Raw Materials, Strategic Components,* and *Structures & Aesthetics.* In turn, these group the 39 *Commodity classes* to which a material can belong. "*The commodity*", as usually called by procurement employees, thus identifies a group of similar vendors and their respective assigned buyers. The buyer is the interfacing agent between Whirlpool and the specific vendor, handling all commercial relationships, official communications and eventual contingencies. Multiple vendors can be assigned to a buyer, who finally reports to her commodity manager.

Fig.3.3. *Cassinetta plant map*

On a monthly basis, each commodity team redacts and updates the new version of the MPV document for the months ahead based on actual consumptions and forecasts. The widespread of the COVID pandemic especially in the North-Italy area, where most of the European supply-base lives, justified additional communicational needs to monitor sudden infections outbreaks that might impact supplied capacity, threatening business continuity. The Whirlpool Crisis Team was thus established in November 2020 to get weekly phone reports from all the EMEA-based vendors about the current capacity status and anticipate potential issues to buyers. Later in April 2021, this process was partially automated by the author during the internship period at the company Procurement Office, developing an automated Google-based survey capable of self-managing the entire stream of data end-to-end for all non-critical suppliers, eliminating the need for 300 calls per week on average.

Commodities	
Chemicals, Resins, Paints & Enamel	Mechanical Components
Steel	Heating & Glass
Plastics	Rubber &Houses& Literature
Electronics	ELME
Metal Stamping	Wire Harness & Power Cords
Cooling & Gas Systems	Packaging
Motors & Pumps	

Tab. 3.2. *Some of the Whirlpool central commodities*

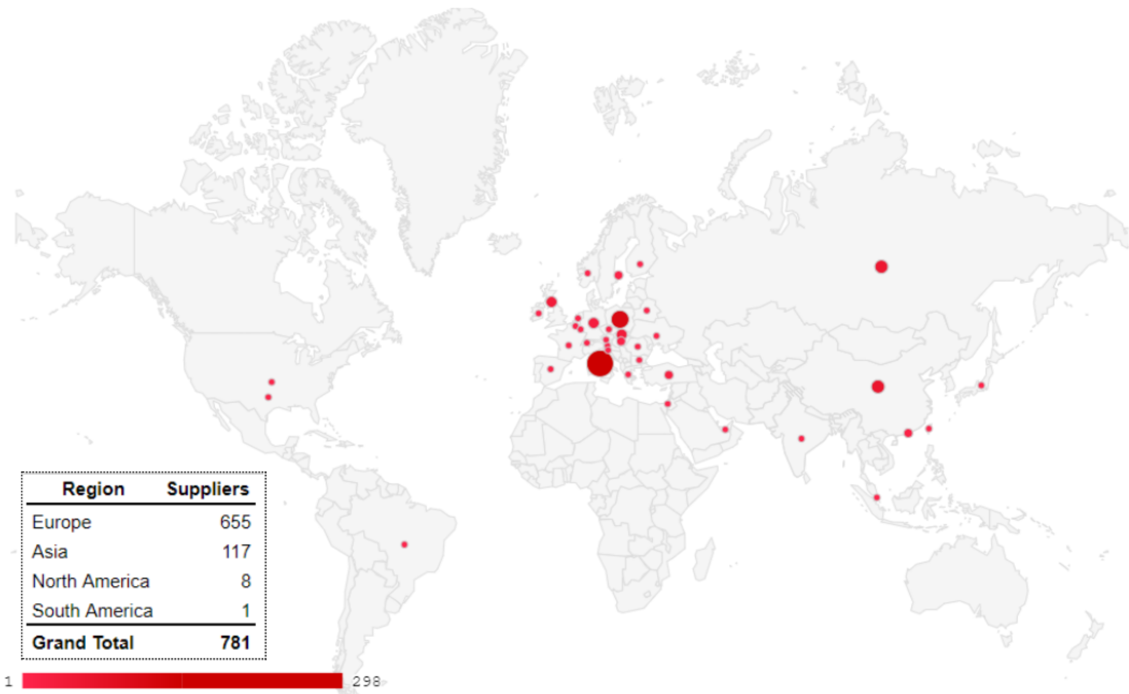


Fig.3.4. *Whirlpool EMEA global supply base*

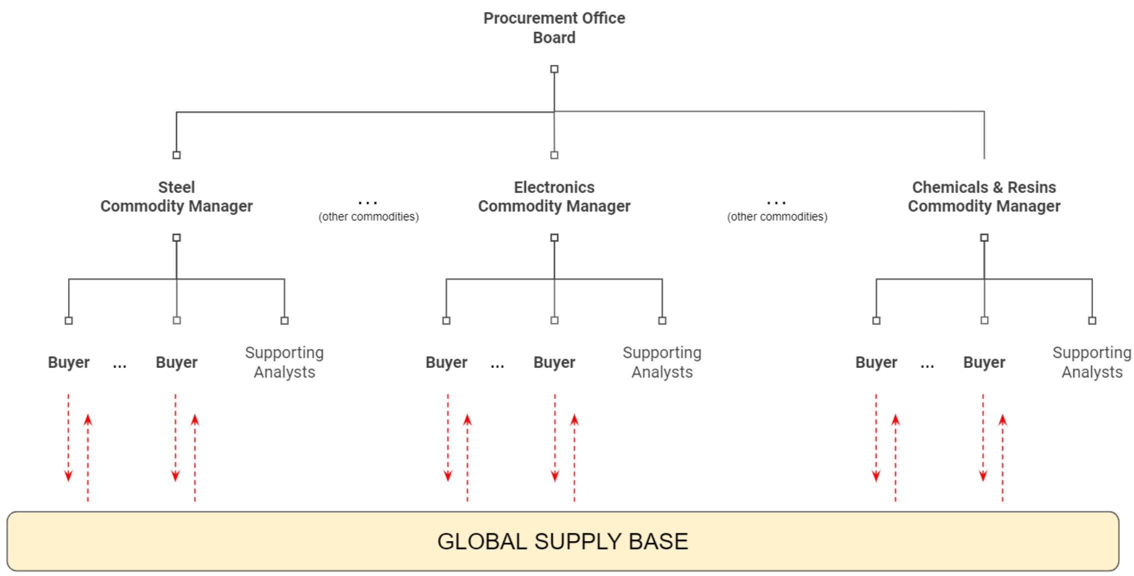


Fig.3.5. *Simplified Procurement Office organisational chart*

From a supply-chain perspective, all items are categorised according to many criteria. First, the overall inventory is divided between *components* and *finished goods*. All items are tracked over multiple dimensions, which are all stored and managed through the SAP ERP system and other in-house developed SAP-integrating tools.

Components and purchased items are first divided into *Lead Time classes*, distinguishing between *Long Lead Time items* (LLT) and *Short-Medium Lead Time items*

(SMLT). While Whirlpool has complete visibility of its purchasing and manufacturing lead times, surprisingly the items are assigned to the two categories using a "responsibility principle" instead:

1. An item is SMLT if it is managed directly by factories
2. An item is LLT otherwise.

This particular approach made sense in terms of semi-components handled within production lines but generated inconsistencies and misleading results when extended to purchased items. Put it simply, a container of "high-running material" from China (e.g. Compressor pumps) would be labelled as SMLT even if it would take more than 50 days to be unloaded (Fig. 3.6).

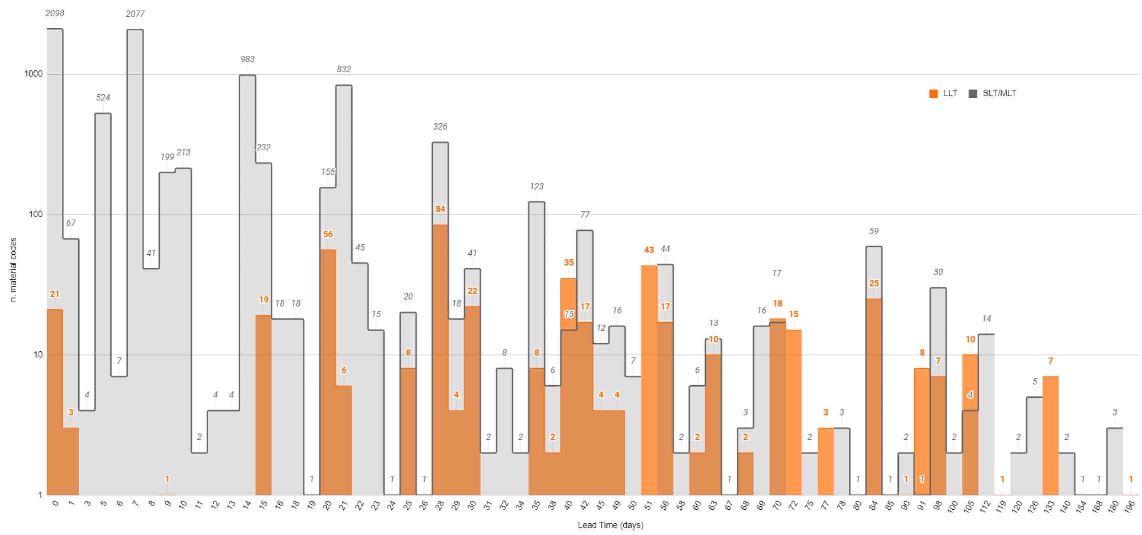


Fig.3.6. *Lead times overlapping definition (logarithmic scale on the vertical axis)*

Components are then further classified accordingly to their *consumption velocity*, distinguishing among:

1. **High-Runners**, components with high consumption rates and inventory levels usually within SS levels plus their cycle stock;
2. **Slow-movers**, components with slow-to-lumpy consumption rates;
3. **Blocked**, components not available for consumption due to several reasons like quality checks, reworks or reshuffling between plants;
4. **Over-Requirement**, components with inventory levels above the SS level plus their cycle stock;

5. **Obsolescence Risk**, components with no consumption 3 months back and no future requirement on-sight;

6. **Obsolete**, components with no consumption 12 months back and no future requirement on-sight.

The ABC-XYZ standard classification is also applied upon 1-year back volumes to supplement the previous categorization, applying a Pareto approach to inventory:

1. **A-items**, high-runners building up to 80% of total volumes;

2. **B-items**, remaining SKUs building from 80% to 90% of remaining total volumes;

3. **C-items**, remaining SKUs building the last 10% of remaining total volumes;

4. **X-items**, "stable", SKUs presenting a Coefficient of Variation of volumes between 0 and 0.5;

5. **Y-items**, "seasonal", SKUs presenting a Coefficient of Variation of volumes between 0.51 and 1;
6. **Z-items**, "lumpy", SKUs presenting a Coefficient of Variation of volumes above 1;

If not otherwise specified, the ABC-XYZ matrix combinations are used to set desired Service Levels for each item in all markets. Differentiation is done here between *freestanding items* and *built-ins*, respectively identifying items consumed/sold separately or in a bundle with other products (e.g., a kitchen assembly is a built-in bundle of finished products and components). In other words, built-in finished goods must all be available at the same time to ship an order.

Service Levels	X	Y	Z
A	Core *98%*	Core *98%*	Customized *95%*
B	Core *98%*	Small runners *95%*	Sporadics *90%*
C	Small runners *95%*	Small runners *95%*	Sporadics *90%*

Tab.3.3. *Service Level setting for Freestanding items*

Finally, arrival and planned consumption dates are intersected to form a *bubble-chart matrix* (Fig. 3.7) highlighting mismatches between planned consumption and the current inventory position, delimiting 4 priority areas, namely:

1. **Green area**, components received within 4-weeks back or currently in transit whose consumption is scheduled within 3-weeks ahead. All components should lie in this area, maximising turnovers and ROA.

2. **Grey area**, components received until 5-weeks back whose consumption is scheduled within 3-weeks ahead. This area represents past inefficiencies that will-be/must-be recovered in the next future.

3. **Yellow area**, components currently on hand or in transit whose consumption is scheduled from 3 weeks ahead. This area highlights materials that might build excess in the next future, defining a warning zone.

4. **Red area**, components currency on hand or in-transit which have no consumptions scheduled. No components should lie in this area.

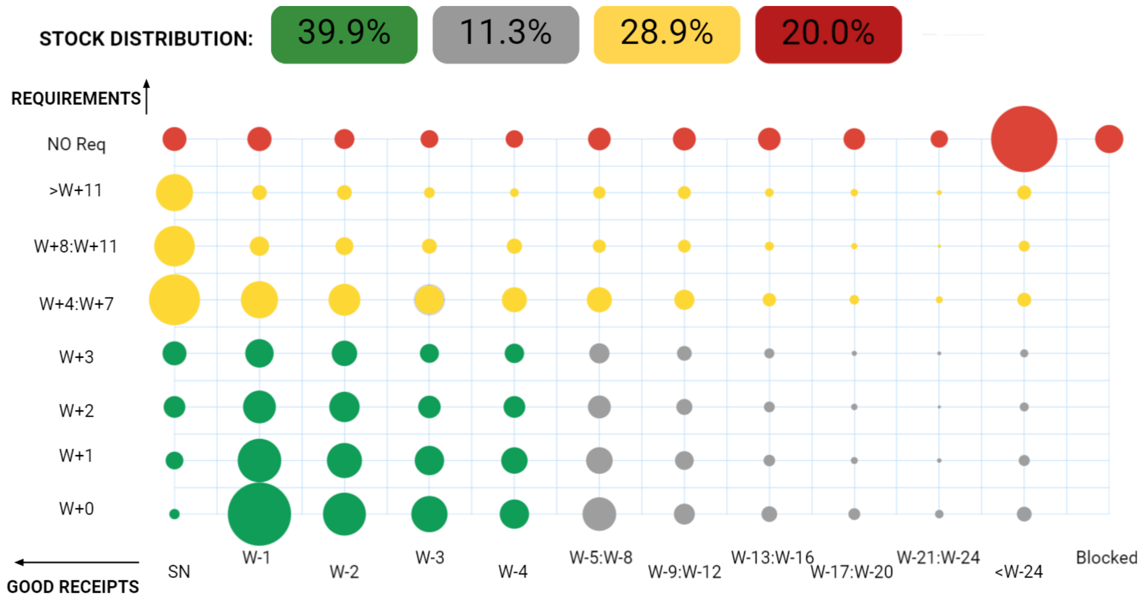


Fig.3.7. *Bubble-chart highlighting excess accumulations and improvement areas. Bubbles areas are proportional to SKUs frequency.*

For the finished goods the classification is much streamlined and follows the *product life-cycle stages*. Chronologically, each product moves into the following classes:

(the following phase descriptions are simplified on purpose)

1. **Violet**, the new product introduction (NPI) request is released, defining all functional requirements and "to-market" dates;

2. **Orange 1**, NPI approval phase and product parts costing estimations. Rejections redirect to the violet stage;

3. **Red**, market introduction dates range approval. Rejections redirect to the violet stage;

4. **Orange 2**, product specification approval. Rejections redirect to Orange 1;

5. **Orange 3**, detailed product specification definition and registration into SAP;

6. **Orange 4**, production ramp-up confirmation;
7. **Yellow**, testing units send to market-relevant clients, creation of product images and literature;
8. **Green**, last BOM updates, APO setting for production plans generation, product life starts;
9. **Brown**, phase-out process and production ramp-down;
10. **Black**, product dismissal.

Green and Brown products are then divided into 2 additional categories:

1. **Blocked,** finished goods ready to be shipped to the downstream nodes (e.g. Regional Warehouses, Distribution partners, Commercial partners, …) but waiting for quality checks;
2. **Undeclared**

In conclusion, the total stock available is classified based on its physical position defining
1. *on-hand,*
2. *in-transit*,
3. *on-consignment*, and
4. *subcontracting located-to-suppliers*

quantities.

3.3.2. The Inventory Growth at the Cassinetta plant

The COVID era showed the complexity the supply chain environment can reach in a fraction of time, cascading disruption on all nodes of modern long supply chains and questioning their resilience built upon the assumptions of the so predicated Toyota model of Just-In-Time (P. S. Goodman). The 6-days obstruction of the Suez Canal by the EverGreen 20.000 TEU ship (Fig. 3.8) in March 2021 gave the definitive hit on the already weakened supply-base suffering from the still-ongoing Chinese materials "*shortage of everything*" triggered by the 2020 COVID pandemic. Metals, electronics, plastic and chemicals supplies suddenly became the most scarce resources, rapidly experiencing skyrocketing price increases. The March 23rd price quotation of metal - just before the Suez Canal event - fluctuating around 120 USD/q jumped to 180 USE/q in 2 weeks, peaking to 208.94 USD/q on May 11th and stabilising around 170 USD/q after it. In comparison, the 2020 average price set to 95 USD/q, peaking to 118.99 USD/q end-of-year, presenting a variation coefficient of 8.66% against 17.25% in 2021 (Fig. 3.9). These harsh market conditions induced extreme competition among all players in securing volumes, pushing some of them also into contracting materials without a previously agreed-upon price. That is, willing to buy materials at any future price to avoid production stoppages. Some of the suppliers' answers to the Crisis Team weekly survey, during that period, are reported below

" We get shortage of steel plastic and trimetal for electrical contacts ; we are every day insisting and optimising our process to avoid to produce parts for buffers and only the necessary ordered pieces "

24 May 2021

" We are running in an overbooked situation , we may have some delays "

31 May 2021

" There could be some general delay in delivering some products due to the big increase of requests"

3 Jun 2021

" We are asking all customers to provide forecast requirements, and have increased stocks of all strategic materials "

6 Jun 2021

" Polypropylene label material sourcing has become a challenge with extending lead times "

6 Jun 2021

" We are struggling the transport cost increase via container from Asia low availability of container has increased significantly the costs "

11 Jun 2021

" Most of the raw materials are increasing in price and with limited availability. If we do not pay more for the materials we cannot ensure the continuity of supply "

13 Jun 2021

" The raw material shortage is impacting us, and the Forecast is very volatile and imprecise "

17 Jun 2021

" DUE TO OVERBOOKING SOME ORDERS MAY HAS DELAYS "

21 Jun 2021

" Delivery time for raw material is at the moment for some type of material more like 8 weeks "

23 Jun 2021

“ We do not have sufficient raw materials from Whirlpool for producing the running orders ”
3 Aug 2021

“ DELAYS ON FERRITICS GRADES ARE EXISTING SPECIALLY ON AISI 439 ”
10 Aug 2021

“ The supply chain management is still a challenge ”
22 Dec 2021 (6 months after the Suez accident and the surge in Asian shortage)

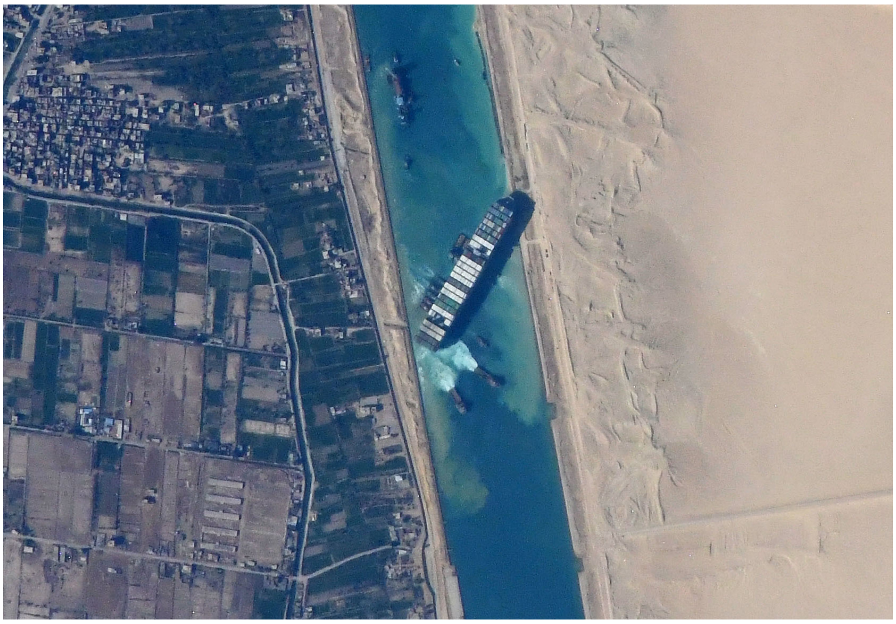


Fig.3.8. *Ever Green obstructing the Suez Canal, By NASA JSC ISS image library*

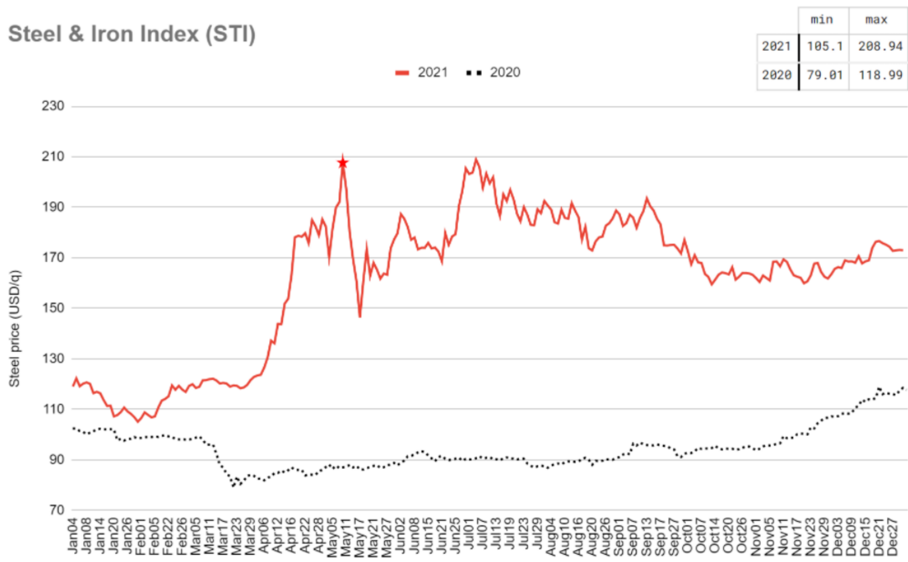


Fig.3.9. *Steel price quotation comparison between 2020 and 2021. Source: Google Finance*

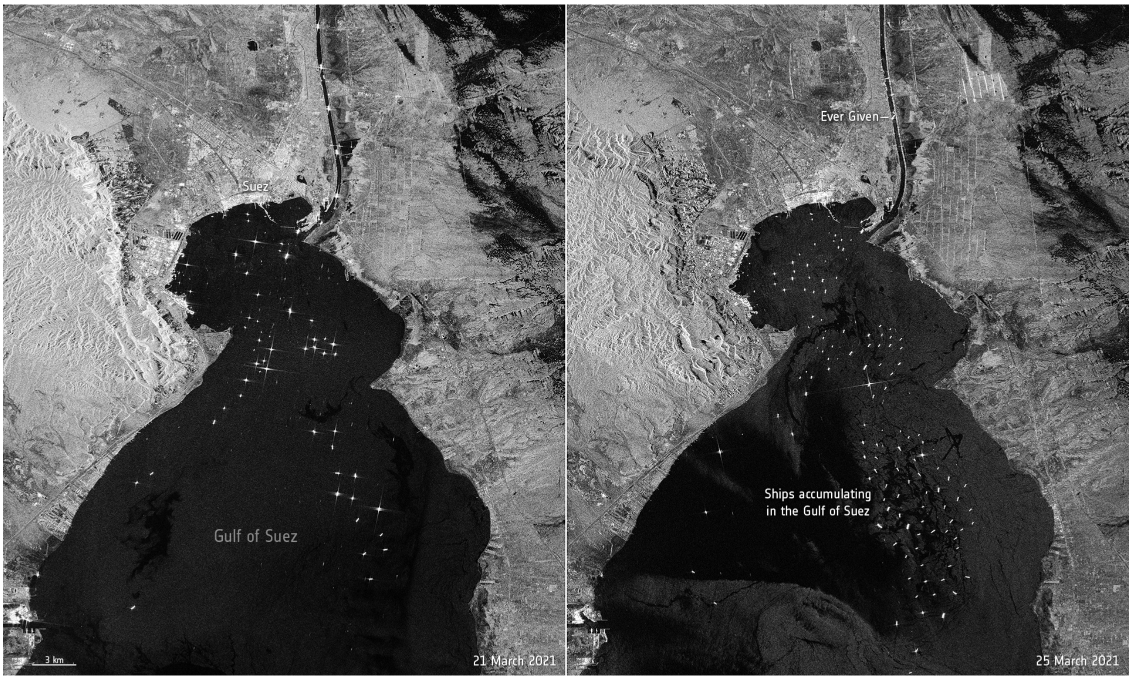


Fig.3.10. *Traffic jam in the Gulf of Suez during Evergreen obstruction, by Contains modified Copernicus Sentinel data 2021*

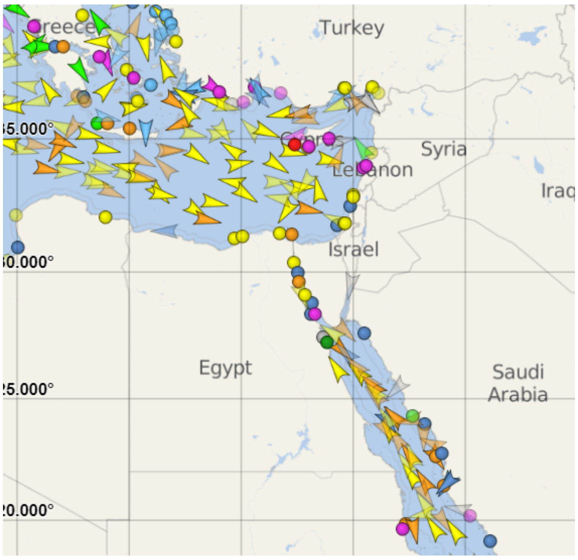


Fig.3.11. *Extracted from Whirlpool internal report about Suez canal traffic in March 2021*

The sharp context partially described above extremely challenged the purse of both Procurement and Integrated Supply Chain yearly strategic goals, respectively:

Reduce costs and excess accumulations *(Procurement)*

Ensure the business continuity, *at any cost* *(Global Supply Chain)*

somehow proving the executives' interest in preventing the creation of the bimodal distribution: procurement will take care of excesses while the integrated supply chain of shortages. Yet under such circumstances these two sides of the coin seemed inevitably contrasting each other.

Evidence about the bimodal distribution upon Whirlpool inventory traces back to early 2000's, when the Whirlpool Corporation started to turn its supply chain network to a global and "fully-integrated" scale, giving birth to the Integrated Supply Chain Division. The at time supply-chain project director, J. B. Hoyt once declared (G. H. Anthes) "We had too much inventory, too little inventory, wrong inventory, right inventory/wrong place, any combination of those things [...] sales department would accept even worse performances from supply system if they would just be consistent rather than wildly bouncing back and forth between good and poor production and shipping plans", strongly recalling the bimodal scenario.

Nowadays, the EMEA inventory management and strategy is led by Matteo Coppola who constantly pushes the supply chain team to twist around the "*guiding principle to inventory strategy*" of whether

" Is inventory investment maximising the organisation's cash generation (margin), protecting market share and service objectives (customers)? "

and defining supply chains as

"*the global network used to deliver products and services from raw material to end customers through an engineered flow of information, physical distribution and cash. A team, a rhythm, discipline and method. All led by a clear purpose and data-driven decisions.*"

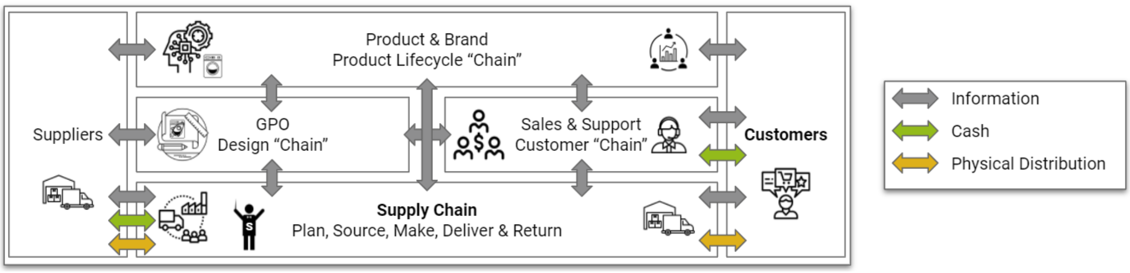
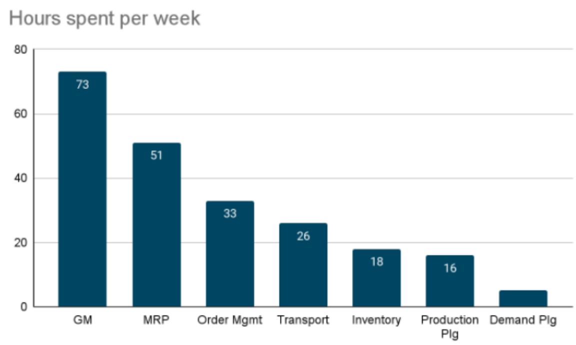


Fig.3.12. *Whirlpool view of its supply chain*

On a monthly basis, the whole EMEA inventory status is reviewed with the Integrated Supply Chain division and all commodity leaders. Some recurring key points keep emerging at each review - among many others. Firstly, is how heterogeneous the decision-making processes are regardless of the big efforts done in centralising information, leading to a disaggregate, non-uniform and difficult-to-review operational response which was causing piling mismatches between the planned Whirlpool business strategy and its actual performances. Secondly, there was a strong need to "*rebuild inventory as an asset from a liability*".

The most impacting inefficiencies in decision-making were attributed to expedition requests that often later turned out to be not extremely urgent, building expensive excesses. These requests were tracked completely manually and on separate worksheets between factories management, finance and planning. Regardless of the best efforts deployed by all actors to make all information needed as clear as possible, nobody in the chain would like to take the responsibility to delay an expedition request just because "checking is difficult" while the potential risk of stopping production is on the way. The urgency nature of the request coupled with the slow reviewing process made unclear what was necessary and what wasn't. On the procurement side, many commodity leaders reported that "factories escalate everything to buyers almost every day". Mapping the "as-is" state of the currently in-place decisional processes identified the existence of almost 90 different reports in use, most of them made of extremely large spreadsheets that on average took 3 hours weekly to refresh individually. Estimates reported a total amount of 892 hours spent just in reports refreshing, equivalent to 5.5 Full-Time Employees (FTEs) *working solely on that*.

SC function	reports in use
Order management	18
MRP	17
Transport	14
Goods movements	11
Inventory	10
Production planning	9
Demand planning	9
Grand Total	**88**



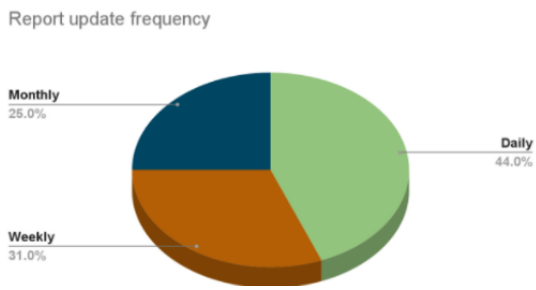


Fig.3.13. *Extracts from "Reports in circulation" survey ran at Whirlpool in August 2021*

On the 2021 roadmap to bring *"inventory back to the primary planning mechanics"* the main changes required are :

1. To focus only on what is relevant, filtering low-frequency noise from real events using a Paretian approach anywhere possible;

2. To redefine target stock levels based on actual consumption rather than forecasts;

3. To reallocate service level priorities, avoiding setting high values also to low-margin SKUs ;

4. To define customer tolerance times and identify time-to-market potentials;
5. To push non-strategic material up in chain using Consignment stocks and Vendor-managed Inventory policies;
6. *"Planning, from Excel to a collaborative planning tool".*

In February 2021, EMEA inventory performances deviated by 30M USD over the profit plan, of which 7M USD totalled by the Cassinetta plants only. The situation gets critical in March peaking to 50M USD, of which 9M USD totalled by the Cassinetta plants, with Cassinetta Refrigeration and Cooking as the top bleeders. On the other hand, an analysis run end-of-January investigating On-Time deliveries showed that roughly 40% of deliveries were more than 2 days delayed and only 45% delivered on time or in advance of promised dates. The March inventory review reports "short-term Excel expediting is consuming planning time [...] there is no visibility on materials in transit and their promised arrival dates".

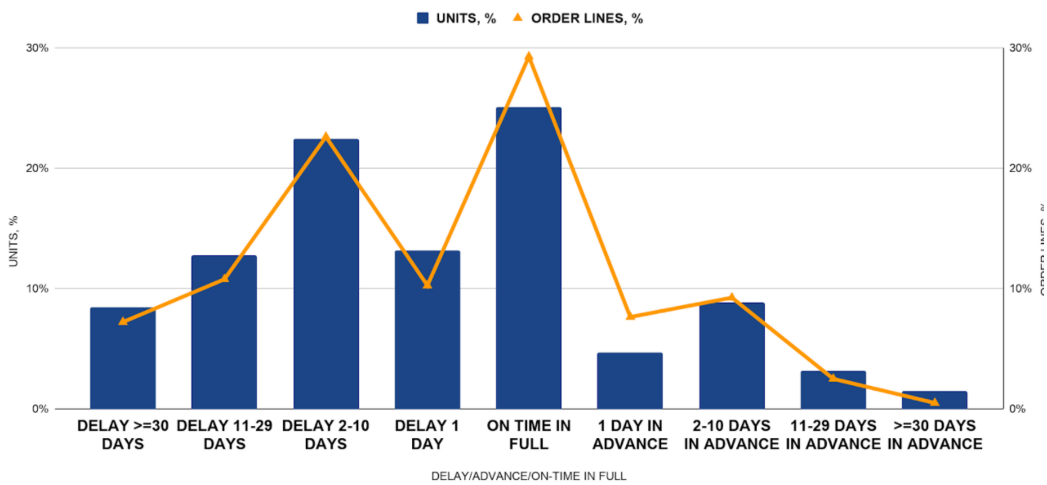


Fig.3.14. *On-time-in-full delivery chart of January 2021*

On May 8th the Cassinetta Plant Manager release the following alert by email :

> " *It seems quite evident that* ***we have a huge deviation*** *in terms of industrial inventory value in Cassinetta [...] currently the level of saturation of the Central Warehouse* ***is above 80% but it should be even more*** *if we consider the materials which are still stored in external overflow areas, which we need to release as soon as possible [...] Due to the pick of containers we are receiving and the missing capacity to absorb the whole flow in 2 shifts, we opened the 3rd one starting from the current week. [...] We are blocking at the Melzo hub what does not seem urgent. We have an agreement for 10 days of free time. In Melzo today we have 21 containers blocked. 17 will be delivered next week and 10 further will be stopped. [...] It could be really helpful to receive the list of codes in transit with n°of containers because so far we can detect the codes only by checking the paper documents. Indeed* ***we don't have a clear view of what we will receive in the coming weeks.*** "

The central warehouse mentioned was capable of hosting 12.000 pallets, covering a usable total surface area of 105 m^2, the equivalent of thirty-five $3m$ wide housing rooms. A preliminary assessment of the issue listed the production losses of March cascading on April LLT inventory levels and the Suez canal disruption as the main causes of inventory explosion. The study revealed again a bimodal scenario where urgent expedited shipments were called for roughly 2M USD worth of material while most of the orders for SKUs already in excess were postponed or cancelled. Production schedule changed in order to absorb excesses to free up space for the new arriving material.

3.3.3. The pilot DDMRP implementation project in Cassinetta

On May 12th, considering the lack of visibility over the in-transit materials and what seemed uncontrolled expedited shipments, Coppola announced the start of a pilot project taking place on the Cassinetta case. A cross-functional team of Procurement and Supply-Chain would deploy the innovative DDMRP methodology to manage the Cassinetta inventory and create complete visibility over real SKUs in shortage and excess based on actual daily consumption, preferring a "*roughly right rather than precisely wrong*" analytical approach. The pilot would have exploited the already great work done by the Global Information Systems (GIS) department since January on the implementation of a full-fledged Google Cloud-based Data-platform called "*industrial inventory*" linked with the SAP ERP inventory module, so to compute all DDMRP metrics on a simple, customizable-to-needs and accessible to everyone online spreadsheet.

Considering the contingency nature of the pilot and the elevated computing power available, DDMRP logics were applied flat on every SKU, that is, no strategic selection of components in the BOMs was done. Although this approach moved against the DDMRP principle of "to not decouple everything", that was instead crucial to protect the continuation of the project: overcomplicating things requesting a deep review of all product BOMs manufactured in Cassinetta, in a period of high disruption were even visibility over in-transit quantities was limited, would have induced strong policy resistance phenomenons (Sterman, Chap. 1) and dispersed the efforts without attacking the problem. Namely, get "a full-body scan" of the inventory health status. Nonetheless, the implementation did not generate any disagreement, especially among factory management. From their point of view, implementing another "naive" tracking system was not solving their daily problems of trucks stuck at the port and, to a point, at the entrance door of the plant. Rather they would have preferred the acquisition or rent of new warehouse space and worked to reinforce JIT policies to push more material to suppliers.

With the promise of rapidly cutting off both excess and shortages and "*make planners life easier*", Coppola notes that *"the situation has more than demonstrated the need for a radical change in the approach to the problem"*.

Within 2 weeks the team was capable of generating on a weekly basis 2 SKUs priority lists, dedicated to excess and priorities. The lists acted as the only "truth table" from where decisions would be taken. The Paretian approach was at the heart of the SKUs prioritisation.

For excesses, the SKUs - so their relative suppliers - in the list were the ones building up to 80% of total excess value. Excesses quantities - and so their monetary value - were computed for each *i-th* SKU by comparing the actual on-hand vs. the DDMRP on-hand optimal range upper-bound:

$$\text{Excess(i)} = \text{MAX}(0, \text{On-Hand(i)} - (\text{TOR(i)} + \text{YZ(i)})\ \ (\text{units})$$

Shortages were prioritised based on vanilla DDMRP on-hand alerts principles, thus measuring the on-hand penetration into Safety Stocks. 4 priority classes were created:

High-warning,	IF On-hand(i)	<=	10%*TOR(i) ;
Medium-warning,	IF On-hand(i)	<=	25%*TOR(i) ;
Low-warning,	IF On-hand(i)	<=	50%*TOR(i) ;
Potential-warning,	IF On-hand(i)	<=	75%*TOR(i) ;
No-warning,	IF On-hand(i)	>	75%*TOR(i) ;

Shortage quantities were computed for all SKUs in high, medium and low shortage priority as the missing quantities to reestablish half of the safety stock:

$$\text{Shortage(i)} = \text{MAX}(0.5^*\text{TOR(i)} - \text{On-Hand(i)}, 0)$$

LT class	Vendor Name	excess value (kEUR)	cumulative %
LLT	Vendor A	397,939.86	22%
LLT	Vendor B	282,968.60	38%
LLT	Vendor C	235,845.97	52%
LLT	Vendor D	219,255.23	64%
LLT	Vendor E	156,949.30	73%
LLT	Vendor F	144,541.97	81%
LLT	Vendor G	58,070.00	84%
SLT/MLT	INTERNAL	1,619,442.34	51%
SLT/MLT	Vendor C	653,632.46	60%
SLT/MLT	Vendor A	318,017.81	65%
SLT/MLT	Vendor F	289,636.83	69%
SLT/MLT	Vendor B	276,610.71	74%
SLT/MLT	Vendor Z	202,233.44	77%
SLT/MLT	Vendor P	196,461.65	80%
SLT/MLT	Vendor D	180,387.45	82%
SLT/MLT	Vendor G	166,243.52	85%

LT class	SS health	Vendor Name	shortage priority (kEUR)
LLT	0-10%	Vendor J	654.23
LLT	10-25%	Vendor H	28.49
LLT	25-50%	Vendor I	16,420.25
LLT	25-50%	Vendor S	608.51
LLT	25-50%	Vendor X	318.30
LLT	25-50%	Vendor L	88.34
SLT/MLT	0-10%	Vendor A	15,197.22
SLT/MLT	0-10%	Vendor U	5,846.15
SLT/MLT	0-10%	Vendor R	5,102.91
SLT/MLT	0-10%	Vendor Q	3,030.40
SLT/MLT	0-10%	Vendor S	2,807.60
SLT/MLT	0-10%	Vendor P	2,596.68
SLT/MLT	0-10%	Vendor X	1,825.86
SLT/MLT	0-10%	Vendor L	1,616.61
SLT/MLT	0-10%	Vendor E	1,603.59
SLT/MLT	0-10%	Vendor T	967.76

Fig.3.14. *Simplified representation of excess and shortage weekly priority lists. Vendors names are omitted on purpose for privacy reasons.*

MATERIAL	Total Stock Qty	Total Stock Value (EUR)	SUM of Open_sched_Line_Qty	SUM of in_transit_stock_Qty	SUM of SAFETY_STOCK	unit cost (EUR/u)	Total LT (Calendar days)	ADU avrg. (UOM/day)	AD Cost (EUR/day)	Order_Freq. (days)	LT class	LTF	ADU*LT*LTF	Order_Freq.*ADU	Var. Factor
000000400010726245	1129	4890.3764	0	0	0	4	105	0	0	120	LLT	0.25	0	0	0.25
000000400010726348	71	192.5875	1	0	0	3	15	0	0	10.90909091	SLT/MLT	0.4	0.2053333333	0.3636363636	0.5
000000400010726526	15	132.2505	0	0	0	9	0	7	62	6	SLT/MLT	0.4	0	42	0.5
000000400010726528	38	338.7092	0	0	0	9	0	2	17	30	SLT/MLT	0.4	0	55.6	0.5
000000400010726559	592	544.64	0	0	0	1	21	0	0	90	SLT/MLT	0.4	0	0	0.5
000000400010726576	569	2659.3353	3	0	0	5	0	0	1	60	SLT/MLT	0.4	0	10	0.5
000000400010726600	627	616.44	3648	0	120	1	8	31	30	0.1071428571	SLT/MLT	0.4	103.4992	3.300357143	0.5
000000400010726623	4406	3491.755	0	0	0	1	0	926	734	0.01106806862	SLT/MLT	0.4	0	10.24807231	0.5
000000400010726938	72	158.76	0	0	0	2	20	0	0	90	SLT/MLT	0.4	0	0	0.5
000000400010726987	1457	552.0573	32500	0	0	0	20	284	108	0.04678362573	SLT/MLT	0.4	2275.44	13.30666667	0.5
000000400010727031	1265	1139.3855	0	2880	0	1	20	8	7	0.2941176471	LLT	0.25	37.86666667	2.22745098	0.25
000000400010727034	3152	5313.0112	1320	0	0	2	20	28	48	0.1147227533	LLT	0.25	142.0333333	3.258891013	0.25
000000400010727035	4320	3057.264	1500	5250	0	1	20	132	93	0.1390498262	LLT	0.25	658.8	18.3212051	0.25
000000400010727036	1698	1135.962	2250	2250	0	1	20	5	3	1.363636364	LLT	0.25	24.4	6.654545455	0.25
000000400010727037	14528	10094.0544	10500	11250	0	1	20	322	224	0.04098360656	LLT	0.25	1610.083333	13.19740437	0.25

MATERIAL	Top of Red (UOM) - Safety Stocks	Yellow (UOM)	Top of Yellow (UOM)	Green (UOM)	Top of Green (UOM)	Red Base (DOS)	Red Safety (DOS)	Top of Red (DOS)	Yellow (DOS)	Top of Yellow (DOS)	Green (DOS)	Top of Green (DOS)
000000400010822869	154.112	256.8533333	410.9653333	408	818.9653333	2.8	1.4	4.2	7	11.2	11.11918605	22.31918605
000000400010822882	30.296	50.49333333	80.78933333	208	288.7893333	2.8	1.4	4.2	7	11.2	28.83548983	40.03548983
000000400010822884	47.74	79.56666667	127.3066667	272	399.3066667	2.8	1.4	4.2	7	11.2	23.92961877	35.12961877
000000400010823057	78.036	130.06	208.096	100	308.096	2.8	1.4	4.2	7	11.2	5.382131324	16.58213132
000000400010823227	0	0	0	1000	1000							
000000400010823229	50376.144	83960.24	134336.384	33584.096	167920.48	14.56	7.28	21.84	36.4	58.24	14.56	72.8
000000400010823230	523.9416	873.236	1397.1776	2000	3397.1776	14.56	7.28	21.84	36.4	58.24	83.36807003	141.60807
000000400010823421	1.76	2.933333333	4.693333333	300	304.6933333	4.4	2.2	6.6	11	17.6	1125	1142.6
000000400010823882	350.406	584.01	934.416	233.604	1168.02	8.4	4.2	12.6	21	33.6	8.4	42
000000400010823891	782.376	1303.96	2086.336	521.584	2607.92	8.4	4.2	12.6	21	33.6	8.4	42
000000400010823909	0	0	0	16.26866953	16.26866953	0	0	0	0	0	0.2575107296	0.2575107296
000000400010823914	833.504	1389.173333	2222.677333	555.6693333	2778.346667	8.96	4.48	13.44	22.4	35.84	8.96	44.8
000000400010823915	646.0636	1076.772667	1722.836267	1000	2722.836267	11.2	5.6	16.8	28	44.8	26.00363184	70.80363184
000000400010824002	25.5108	42.518	68.0288	150	218.0288	0.56	0.28	0.84	1.4	2.24	4.939084623	7.179084623
000000400010824003	51.1588	85.26466667	136.4234667	150	286.4234667	0.56	0.28	0.84	1.4	2.24	2.46291938	4.70291938
000000400010824039	526.6464	877.744	1404.3904	351.0976	1755.488	11.2	5.6	16.8	28	44.8	11.2	56

MATERIAL	Top of Green (UOM)	ON-hand priority	SS health	shortage priority qty	shortage priority (EUR)	SS APO vs.required	max allow.target	max allow. value (EUR)	excess priority 1	excess qty	excess value (EUR)	shortage value (EUR)
000000400010554142	233.3066667	15.17285531	75-100%	0	0	3.201024328	106.24	113.57056	TRUE	390.6933333	418	0
000000400010554210	0	excess		0	0		0	0	FALSE	0	0	0
000000400010554211	0	excess		0	0		0	0	FALSE	0	0	0
000000400010554214	1985.0496	3.903690203	75-100%	0	0	0	914.3936	1744.571549	TRUE	289.9504	553	0
000000400010554215	2145.373867	5.324003651	75-100%	0	0	0	974.5152	1859.27755	TRUE	782.6261333	1493	0
000000400010554387	61508.76	0.6052254454	50-75%	0	0	0	24603.504	1390.097976	FALSE	0	0	0
000000400010554542	1736.149333	1.79324052	75-100%	0	0	0.1843159421	694.4597333	623.9026244	FALSE	0	0	0
000000400010555027	5410.905	2.888795582	75-100%	0	0	0	1854.025	6512.81902	FALSE	0	0	0
000000400010555032	23987.13333	0.4542713177	25-50%	329.07	1562.621802	0.4268955301	9594.853333	45562.12054	FALSE	0	0	7420
000000400010555038	1063.16	0.4985138643	25-50%	0.474	0.062094	0	425.264	55.709584	FALSE	0	0	0
000000400010555291	1850.528	1.247852314	75-100%	0	0	0	818.948	107.282188	FALSE	0	0	0
000000400010555559	0	excess		0	0		0	0	TRUE	5	3	0
000000400010555795	214.4	21.86507937	75-100%	0	0	1.607142857	90.4	70.63856	TRUE	967.6	756	0
000000400010555881	294.4	9.226190476	75-100%	0	0	0	130.4	95.518	TRUE	330.6	242	0
000000400010556073	18309.13333	1.160440873	75-100%	0	0	0.2730877486	7323.653333	481.164024	FALSE	0	0	0
000000400010556085	0	excess		0	0		0	0	TRUE	250	183	0

Fig.3.15. *Buffer dimensioning and excess/shortages calculation for all SKUs*

The Average Daily Usage (ADU) was computed for each i-th SKU adopting a blended approach, thus averaging past sales with forecasts over a fixed time-horizon of 12 weeks. Sales were extracted from the MB51 and MSEG SAP standard transactions while future requirements were extracted from the Advanced Planning Optimizer (APO) SAP module. An addition to the vanilla DDMRP model was performed by allowing the ADU time-window to dynamically shift more (less) in the past (future) accordingly to item XYZ classification :

	weeks in the past	weeks in the future
X	10	2
Y	6	6
Z	4	8

Tab. 3.4. *The ADU moving window based on items XYZ classification*

SKUs Total Lead Time was computed as the sum of Purchasing Lead time and Manufacturing Lead time.

Lead Time Factors (LTF) were assigned flat to BUY items while 3 Lead-time defined classes were created for MAKE items, resembling the vanilla DDMRP model:

IF *i* is BUY	THEN	LTF(i) = 0.15 ;
IF *i* is MAKE and LT(i) <= 10	THEN	LTF(i) = 0.8 ;
IF *i* is MAKE and LT(i) <= 30	THEN	LTF(i) = 0.6 ;
IF *i* is MAKE and LT(i) > 10	THEN	LTF(i) = 0.35 ;

Note that the shorter the lead time, the higher the LTF assigned to it.

Demand Variability Factors (DVF) were assigned flat to BUY items while 3 XYZ defined classes were created for MAKE items, resembling the vanilla DDMRP model:

IF *i* is BUY	THEN	DVF(i) = 0.25 ;
IF *i* is MAKE and X	THEN	DVF(i) = 0.2 ;
IF *i* is MAKE and Y	THEN	DVF(i) = 0.5 ;
IF *i* is MAKE and Z	THEN	DVF(i) = 0.99 ;

Note that the higher the variability, the higher the DVF assigned to it.

Finally, the Order Cycle Time (OCT) was estimated by counting the number of consumption records registered in the MSEG SAP transaction over a fixed period of 90 days in the past.

$$OCT(i) = 90 / \sum \text{Consumption Movements Last 90 Days } (i)$$

This value was then compared with the Average Order Frequency generated by the model, defined as in vanilla DDMRP:

$$AOF(i) = GZ(i) / ADU(i)$$

Once implemented, the most delicate stages of the pilot started:

1. validating it against current SAP-based scenarios and “people operational knowledge”
2. make it became the real only mechanism of inventory management

The first point required extensive cross-functional meeting sessions where all agents from the factory management to finance, procurement and planning were asked to give their feedback about the figures yield by the model. This process revealed extreme data inaccuracy set in the SAP system, especially regarding wrong MOQs and Lead Time settings. For instance, some EU vendors were considered as “JIT vendors” setting very low transportation

Lead Times in the system (e.g set to 0 to some Italian vendors). It is worth remembering that the ERP system is entitled to release all the replenishment orders and production scheduling plans, running MRP on the given values, thus it is in the strong interest of managers to keep the system up-to-date. While these results might look surprising, this scenario is not a novelty in the supply-chain world (C. Ptak, C. Smith) and it is mostly due to the well-known *nervousness* of the MRP algorithm, one of its main weaknesses. Every night the MRP would be re-run, changing completely the scenario from the previous day, updating orders priority, sometimes generating back-dated orders, generating confusion. What the pilot showed was a tendency behaviour to "keep the system as dormant as possible", using the MRP data as a baseline to then be handled manually on spreadsheets to define the actual operational response. Moreover, the ERP was not designed to massively extract data, usually requiring to browse one SKU at the time on each needed transaction. The lack of "what-if tools" in S&OP was already reported in one of the inventory reviews and justified the investment in a project managed by a consultant to improve the situation. An extensive "massive data cleaning" campaign was thus launched starting from June, with the aim of reviewing all LTs and MOQs set in the system and, when possible, thinking about possible re-negotiation of MOQs based on ADU. In other words, all MOQ greater than ADU were possible candidates for MOQ reductions. While this approach is quite logical, it must be taken into account that MOQs are the result of a negotiation where suppliers try to optimise the overall production line load while the client would desider a "dedicated" infrastructure ready for lot-for-lot orders. These trade-offs strongly drive the final contract awarded price and MOQs. In general, lowering MOQs induce unit prices to increase. The analysis thus required a case-by-case analysis of the trade-offs involved, selecting from which vendor to start the campaign again adopting a Paretian approach.

The second point required the pilot results to be massively diffused among the organisation, giving complete and clear visibility to everyone. A "reporting campaign" thus started in June with the aim to develop two detailed reporting dashboards bisecting all possible aspects of inventory, both at global and individual SKU scale. Finally, the reporting activity was also summarised weekly by emails "*bombarding all actors in the organisation about the current state of things*" to promote actions and reactions.

The reported success of the pilot in reducing the excess creation authorised the extension of it to all EMEA plants, starting from Poprad where a huge obsolescence risk emerged during the summer. Nowadays, one year from the first implementation, the project approach has been completely ported into the GCP data-platform from where it is then applied to all upstream plants, with the aim of starting to develop a distribution-oriented version of it.

3.3.4. The "Industrial Inventory" Google Cloud Data-Platform

Visibility and quality - rather than scarcity - represent the typical major issues related with data in most supply-chain applications. On the other hand, disposing of massive databases does not necessarily guarantee shared and accessible information, or even information in the first place (S. Levi, Chapter.14). Specialised efforts are usually required to summarise data into business knowledge, a role typically outsourced to external consultants guided by company facilitators.

Big players like Whirlpool pull and generate vast amounts of data every day. Thus, its employees are forced to find agile ways to dig into and exploit such abundance while not slowing down the decision-making pace. As shown in Chapter 2, such circumstances coupled with the diversity of business needs over time, led most of the teams building tailored reports to answer leadership specific questions, at the end piling a "reports wall" accessible only to the initial requesting users of the analyses and its developers. Requesting access and support to use and interpret a "never seen before" report or spreadsheet when participating in cross-functional tasks seemed the norm rather than the exception. Because generated by different agents (e.g. planners, buyers, finance, procurement, factories, suppliers) in different locations and time, data were typically scattered throughout many systems, starting from the ERP module of SAP, to its Business Intelligence (SAP BI/HANA) and Advanced Planning Optimisation (SAP APO) modules, Google Sheet, Excel, Tableau, Prime Viewer and many others. The SAP ERP module in particular, where most of the data lived, seriously constrained the data share-ability due to the lack in the ERP design of "massive data extraction" functions. Rather, every ERP interaction could only take place through specific build-in functions, conventionally called "*transactions*" in the SAP jargon. All SAP transactions are identified by specific IDs that surprisingly seemed extremely difficult to retrieve with certainty, being the SAP official website and the online users forum the first confusing places to search for answers. Accessing any transaction typically required prior request of specific grants that needed approval by designed users. Once all set, the most effective means to understand the scope and the data retrieved by the transaction was to launch different combination of its parameters as long as either some reasonable results were returned, guiding a parameters adjustments process in a try-and-error fashion, or the support of a senior user was required to continue or validate the data. It was rather usual that this scenario ended in understanding that the used transaction was the wrong one or that something was missing. For all occasional SAP users, like Team Data Analysts, whose typical workflow is not limited to the use of a single tool, most SAP-including analyses ended up shifting the focus more on reverse engineering the transaction behaviour rather than advancing the initial business question. In case of success, the transactions allowed retrieval of information about single instances and not a panel of objects. Thus, retrieving some kind of data for a family or all SKUs produced even in the same factory would have required multiple reruns of the same transaction, followed by a data export into different Excel spreadsheets for each run, which finally needed to be aggregated in a single one so as to finally run the desidered analysis. What seems like an extreme scenario was instead the case when the design and introduction of a new custom metric, called *Delivery Service Index* (DSI), started. This metric would compare the agreed material delivery dates with the actual ones and estimate the impact of those delays on the production continuity, so as to rank suppliers upon DSI terms.

Given the extraordinary amount of time required even by expert users to retrieve a rather small amount of data, the DSI project was seriously redimensioned and decided to be evaluated on a monthly basis only, somehow losing effectiveness and trust.

Finally, many of the considered "expert SAP users", like buyers and planners, were declaring to only know how to use a subset of its transactions, the ones they occur to use on a daily basis, suggesting that the experience they gained was somehow non-reusable in other business contexts (e.g. finance transactions). Moreover, unavailability of these employees would mean a huge loss for the company's ability to use and interpret SAP, creating high "asset-specificity", both to the tool and the employees.

When "broad business questions" were asked, this data environment typically obliged the analysts to call several meetings with all relevant users to reconstruct the information puzzle. This situation escalated as broadly as the initial query was and, for those applications where massive data extraction were essential (e.g. DSI), custom "Z-transactions" were required to be designed by the Global Information System (GIS) team.

From June 2021, the Whirlpool GSS leadership decided to cut the inefficiencies derived by having so many systems in place and to integrate the majority of those in a single "point of truth", with a strong focus on making SAP data quickly and massively accessible. The resulting Data-Warehouse, essentially a large NoSQL database called "*Industrial Inventory Data-Platform*" (DP), would have lived on the Google infrastructure, also known as the *Google Cloud Platform* (GCP), exploiting the extraordinary indexing, storing and computing capabilities of Google for a rather cheap package compared to its added-value. In this configuration the previous systems would act solely as "data providers" from which data would be pulled and streamed automatically into the new system every night. During the streaming process, normalisation and manipulation of data would be applied to build automatically refreshed reports designed upon leadership requirements. With this system in place, Whirlpool employees of any division (e.g Finance, Integrated Supply Chain, Procurement, ...) would be capable of querying all the Whirlpool knowledge, put it together in easy to make reports, globally accessible and fed by Big (and reviewed) Data, through the reporting tool of Google DataStudio embedded into the DP.

The choice of Google as a provider for data-warehousing rather than Microsoft or Amazon (e.g. Azure, Firebase) determined a strategic win given that the majority of "daily employees routines" in any office were performed using Google products (e.g. *Gmail* for internal and external communications, *Google Sheets* for internal reporting, *Google Drive* for sharing the knowledge base, *Google Analytics* to monitor e-commerce, ect) thus providing rapid coupling of the innovation with existing solutions.

Fig. 3.15. shows the Industrial Inventory "SQL interface", powered by the Google BigQuery computing engine, where tabular data can be extracted on request using standard SQL-statements.

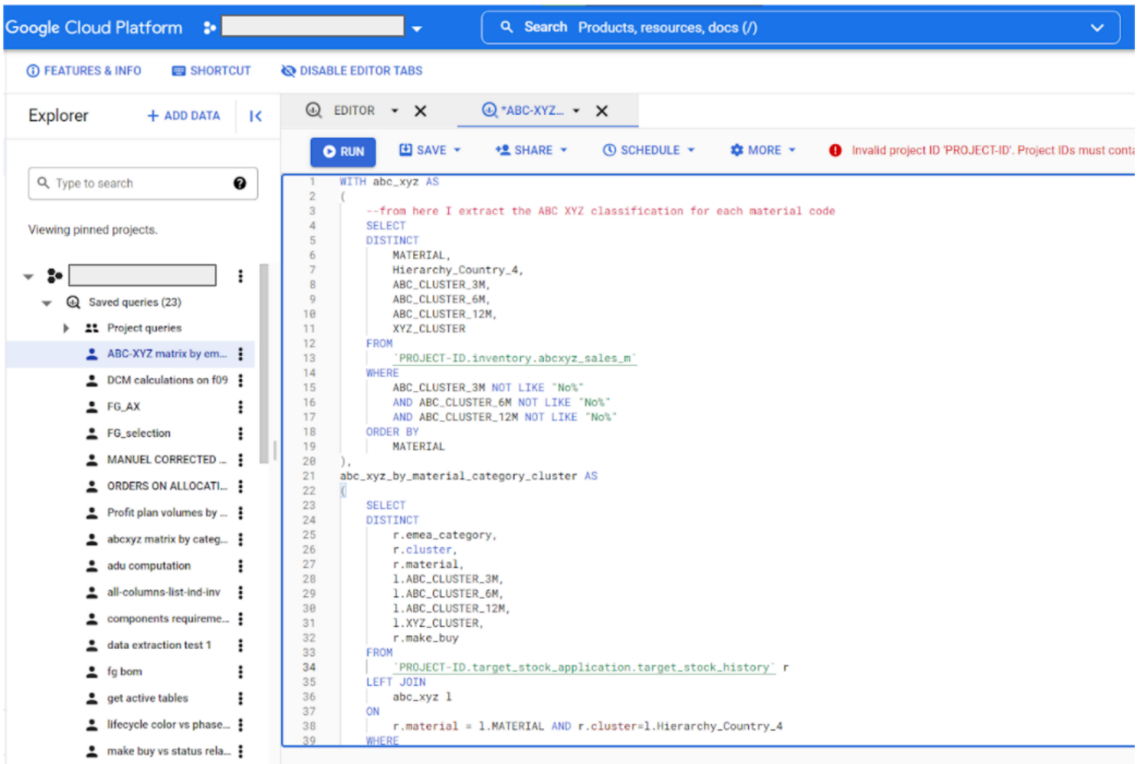


Fig.3.15. *The SQL Workbench powered by BigQuery to extract knowledge from the DP*

SQL stands for "*Standard Query Language*" and while at first it can feel like an additional barrier to information, it instead provides a generalised language to explore any tabular data-structure, regardless of different implementations and business environments, being considered an industry-standard everytime there is the need of serious (and massive) data manipulations. Moreover, extensive support is provided for SQL on free peer-reviewed online forums like StackOverflow.

Upon this generalised language it comes one of the biggest advantages of the Industrial Inventory DP : the flow of relevant information is organised under a "natural language" structure. Thus, extracting current inventory levels trends for all finished products produced in all the Cassinetta Plants during February 2021 looks alike the following query

```
SELECT
        material, commercial_code, material_short_description, emea_category,
        plant, plant_desc, plant_type, storage_location,production_line,
        On_hand_qty, intransit_qty, moq,lt_transport, lt_manufacturing, unit_price,
        creation_date
FROM `IND_INV_FG.stock_application.L2.F_target_stock`
WHERE
        plant in ("C020", "C021", "C022") AND
        creation_date BETWEEN "2021-02-01" AND "2021-03-01" AND
        lifecycle_color = "Green" AND
        make_buy = "MAKE"
```

which returns the matching *tabular data* in Fig. 3.16.

Job information | Results | JSON | Execution details

Row	material	commercial_code	material_short_description	emea_category	plant	plant_desc	storage_location	production_line	on_hand_qty	intransit_qty	moq	lt_transport	lt_manufacturing	unit_price
1	859991548130	IBU 92 V	Oven - IBU 92 V	COOKING	C021	HQ Cassinetta CDC (FG)	05 - CDCs	Minerva 67 lt - Stan	0.0	0.0	48.0	1.0	31.0	0.0
2	859991544370	W7 MS450	Oven - W7 MS450	COOKING	C021	HQ Cassinetta CDC (FG)	05 - CDCs	SAUNA	4.0	0.0	6.0	1.0	10.0	320.2
3	852565641000	AKZM656IX	Oven - AKZM656IX	COOKING	C021	HQ Cassinetta CDC (FG)	05 - CDCs	Minerva 67 lt - Stan	5.0	0.0	48.0	1.0	10.0	149.88
4	852575641000	AKZM756IX	Oven - AKZM756IX	COOKING	C021	HQ Cassinetta CDC (FG)	05 - CDCs	Minerva 67 lt - Stan	72.0	0.0	48.0	1.0	10.0	138.0
5	859991560800	JJW2424HL	Oven - JJW2424HL	COOKING	C021	HQ Cassinetta CDC (FG)	05 - CDCs	Oxford NAR (Line 4)	0.0	0.0	24.0	1.0	10.0	0.0
6	859991560810	JJW2424HM	Oven - JJW2424HM	COOKING	C021	HQ Cassinetta CDC (FG)	05 - CDCs	Oxford NAR (Line 4)	52.0	0.0	24.0	1.0	10.0	519.15
7	859991560670	JJW6024HL	Oven - JJW6024HL	COOKING	C021	HQ Cassinetta CDC (FG)	05 - CDCs	SAUNA	72.0	0.0	24.0	1.0	10.0	608.27
8	859991560660	JJW6024HM	Oven - JJW6024HM	COOKING	C021	HQ Cassinetta CDC (FG)	05 - CDCs	SAUNA	64.0	0.0	24.0	1.0	10.0	655.84
9	859991539570	W11 MS180	Oven - W11 MS180	COOKING	C021	HQ Cassinetta CDC (FG)	05 - CDCs	SAUNA	0.0	0.0	8.0	1.0	10.0	0.0
10	859991604230	W7 MSIXOC	Oven - W7 MSIXOC	COOKING	C021	HQ Cassinetta CDC (FG)	05 - CDCs	SAUNA	23.0	0.0	24.0	1.0	10.0	317.82
11	869991031820	GMA 9522/IX	Hob - GMA 9522/IX	COOKING	C021	HQ Cassinetta CDC (FG)	05 - CDCs	GAS - EX CASS	0.0	0.0	72.0	14.0	15.0	0.0
12	869991548560	KHIAF 86500	Hob - KHIAF 86500	COOKING	C021	HQ Cassinetta CDC (FG)	05 - CDCs	INDUCTION (no i100)	0.0	0.0	16.0	14.0	15.0	0.0
13	869991548660	KHIAF 87700	Hob - KHIAF 87700	COOKING	C021	HQ Cassinetta CDC (FG)	05 - CDCs	INDUCTION (no i100)	0.0	0.0	48.0	14.0	15.0	0.0
14	858547629000	AKZ 476/IX	Oven - AKZ 476/IX	COOKING	C021	HQ Cassinetta CDC (FG)	05 - CDCs	Minerva 55 lt - UTC	2.0	0.0	9.6	1.0	31.0	134.02
15	858547629000	AKZ 476/IX	Oven - AKZ 476/IX	COOKING	C020	HQ Cassinetta FDC (FG)	06 - FDCs	Minerva 55 lt - UTC	59.0	0.0	9.6	1.0	31.0	134.02
16	858548329000	AKZ 483/IX	Oven - AKZ 483/IX	COOKING	C021	HQ Cassinetta CDC (FG)	05 - CDCs	Minerva 55 lt - UTC	668.0	0.0	24.0	1.0	10.0	134.25
17	858551329000	AKZ 513/IX	Oven - AKZ 513/IX	COOKING	C021	HQ Cassinetta CDC (FG)	05 - CDCs	Minerva 55 lt - UTC	118.0	0.0	48.0	1.0	10.0	142.02

Fig.3.16. *Tabular query results example provided by the DP*

Tables of over 1M rows can easily be exported into common spreadsheet apps using .csv files, generated automatically by the DP after each query, or be directly assessed using *Google DataStudio*, as in Fig.3.18.

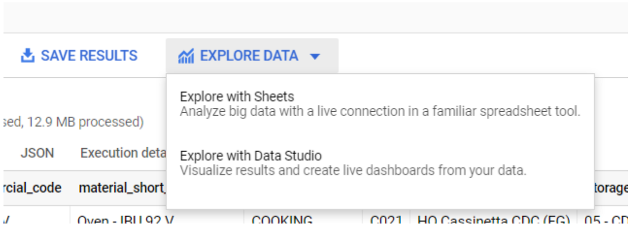


Fig.3.17. *Easy query results export*

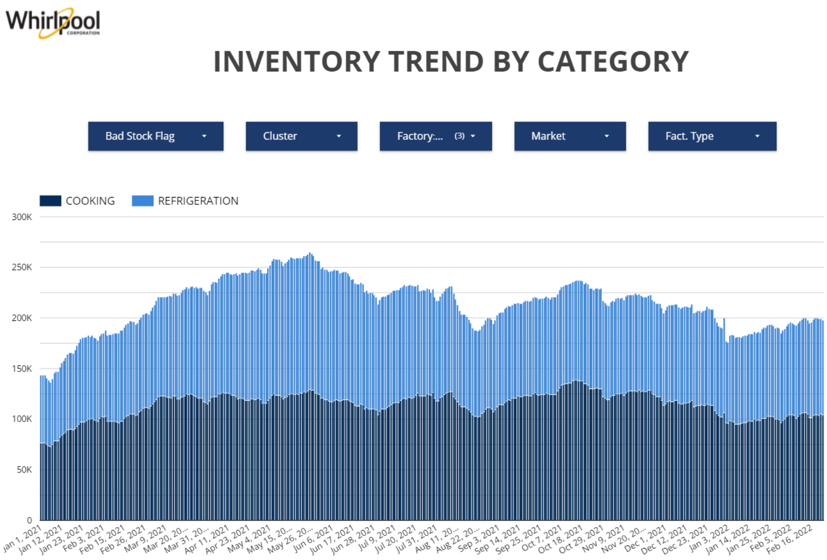


Fig.3.18. *Direct Reporting from queries in DataStudio, Whirlpool official reports.*

The DP was built as of best practices in data-warehousing: raw data coming from the different the Whirlpool individual systems are sequentially moved along 3 different *layers*, called respectively L0, L1 and L2, where "L" stands for "layer" and the trailing digit represents the "*layer elevation*". The information content - its quality and relevance - of data in each layer rises as it gets more elevated, thus final users can find all relevant and certified pieces of information by querying L2 directly. For these reasons, SQL-tables stored in L2 are also called "*fact tables*", identified by a leading "F_" in their name.

Data is moved among layers automatically through a set of time-based scheduled queries called *procedures*. Procedures typically do not retrieve data directly from the source SQL-table, but they use a specified "manipulated version" of it, called *view*. Views hereditate their name from the fact that they can be seen as "a way of looking into the tables". They essentially are "template SQL queries" saved on the GCP that *preprocess* the raw data to be streamed to another location, typically a higher layer in the DP. The main difference between SQL-tables and views is that tables are used to store data provided with a certain format, while views do not. Once a view is run against a table (or a set of them), its result is a temporary table that can be either handled by procedures, saved into a new table, also called *materialised view*, or outputted to the user invoking it. After this, views results are discarded, requiring to re-run the view if the output is needed again. Views are extremely versatile and allow to really create knowledge out of raw data, indeed a typical use of them is for aggregating data from multiple SQL-tables in order to compute aggregated KPIs.

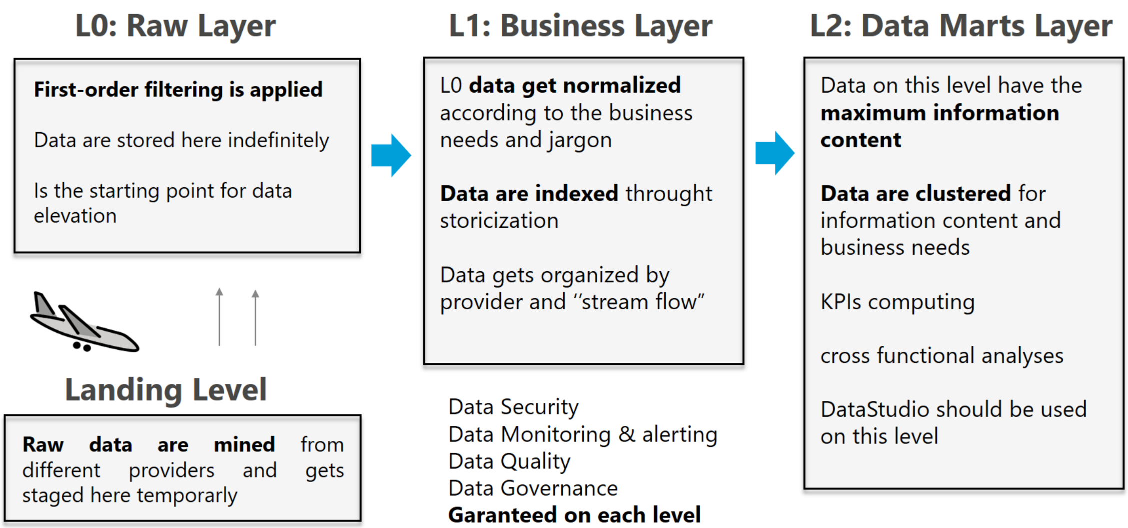


Fig.3.19. *L0, L1, L2 data platform structure. Views and procedures are visualised by blue arrows.*

The whole structure of the Industrial Inventory cannot be disclosed but a general view of the main fact tables is provided.

At the highest level, the DP is divided into 2 pillar projects, the "*ind-inv-fg*" dedicated to the finished goods and the "*ind-inv-comp*" for components up to raw-materials. Even if both projects are still under constant development, the components one still represents a WIP, thus it was considered less in this work.

Both projects are further divided into 6 main modules, also called *datasets*:

1. **Reporting Dataset**. It groups all the views used to construct automatic reports, providing insight and historical trends for excess and shortages, orders on-allocation, obsolescence risk, and so on.

2. **Target stock Dataset**. It is the most important dataset were data from all other datasets are merged together into a final overarching fact table called "*target_stock*", deriving for each good the ABC-XYZ classification, Direct Contribution Margin (DCM), Net Flow Position (NFP) and Average Daily Usage (ADU) at each plant and storage location, distribution related data, plants inventory levels, good and plant metadata, and so on. This represents the L2.

3. **Inventory Dataset**. It groups all tables and views needed for segmenting the inventory by the criteria presented in Chap. 2. Together with the Finance dataset, it completes the L1.

4. **Finance Dataset**. It groups all tables related to financial metrics, like aggregate historical sales by market, approved forecasts derived by the Open Demand Planning (ODP) process, profit plan targets, and so on. Together with the Inventory dataset, it completes the L1.

5. **BOM Dataset.** Still a WIP dataset, in its final version it will be the connecting point between finished goods data (intermediate assemblies for the components module) and their child components (raw materials), exploiting BOMs stored in SAP.

6. **External Sources Dataset**. It represents the L0 where data from SAP material management (MM) module, SAP BI, and other providers, land.

For what regards SAP data, the DP get refreshed based upon multiple "cycles":

During the first week of the month, the demand forecasts are updated upon release of a new "*consensus forecast*" by the Demand Planning (DP) team, made by S&OP leaders, GSS analysts and planners, Procurement and Finance analysts and Top Management. This forecast is constituted of both Make-To-Stock (MTS) requirements and Make-To-Order (MTO) ones that shall take place in the following 12-months of current date. At each release, the monthly consensus forecast gets loaded into the Advanced Planning Optimizer (APO) SAP module, which based on all products global lead times, frozen shipping agreements (quantities that cannot be updated by the optimizer), current production load, target inventory thresholds and current inventory levels in each plant, distributes the additional production workload. This process defines the "*production plan*", thus all the finished goods requirements for each working day, also known as the "*independent demand*".

Every night, the MRP module of SAP based on the production plan input and the current production output, walks backward into each finished good BOM so as to generate the so-called *"dependent demand"*, thus the components requirement up to raw-materials in order to fulfil the production plan schedule. The dependent demand for raw-materials gets compared with each supplier purchasing agreement conditions (e.g. MOQ, Lead Time, ect.) so as to generate what are known as the "*open schedule lines*" (OSL). Both schedule lines and purchasing agreements are produced externally from the DP. Purchasing agreements are established after a negotiating activity happening between buyers and suppliers. Schedule lines instead represent a "derivative operative contract" of the purchasing agreement, where multiple schedule agreements can be released based on the same purchasing terms. In each schedule line specific quantities, promised delivery dates and awarding price are fixed. Every shipping notification can be approved or reviewed and updated by planners, flagging it as frozen. Moreover, planners have visibility on projected on-hand, by invoking the ZSHORT SAP transaction, and basically all information relative to materials.

All these take place on SAP. The DP updating processes intercept the summary of the daily SAP operations by pulling data every night, reversing the logic described above. Thus, "closing-day" materials data get collected from the MM module of SAP, massively launching (mainly) the MB51 and MSEG transaction against all codes.

From the MB51, material movements (e.g. consumptions, reverse logistics, material reworks, internal reshuffling) are retrieved and analysed in order to quantify ADU, current inventory levels and material obsolescence rate. The obsolescence rate is estimated on a monthly basis as the fraction of the material direct costs accrued since the last material movement registered in the system. Materials can "age" up to 12-months before being considered fully obsolete, thus needing to be scrapped either by components reselling, scrapping or shredding. Material ending in those scenarios counts as complete sunk costs given that the gains from reselling or scrapping hardly cover the total direct (e.g. purchasing price, transport costs, customs importing duties) and indirect (e.g. storage costs, labour, machine time) costs generated by them over time. Thus, a metal coils pallet with material costs of 30.000USD that sits in the same storage location since 4-months without any picking operation, on current date accrued an

$$\text{Obsolescence Risk} = (4/12) * 30.000 \text{ USD} = 10.000\text{USD}$$

From the MSEG, data about ODPs and OSLs quantities, delayed order on-allocation and portfolio quantities are retrieved and used to compute the Qualified Demand and Order Frequency upon a 90-days time-window.

Upon this L0 refresh, the whole inventory segmentation gets recomputed, as long as the ABC-XYZ classification and the all material DCMs. As introduced in Chapter 2, DVF and LTF are deduced from the ABC-XYZ matrix.

At this stage, all single bits of information are ready to be merged in the target stock fact table. Here is where all the DDMRP inventory thresholds and net flow position get determined on a daily basis. Once L2 is refreshed, the reporting views are immediately able to lay out the updated trends.

Chapter 4

System Dynamics : Understanding Complex Systems

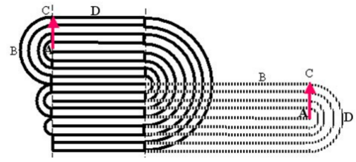
*"**Experience**, something you get **after** you need it. "*
Cit. Anonymous

System Dynamic sits at the core of this study, thus in this chapter a general overview of it is given to the reader after having explained why simulations play a pivotal role in decision-making. The basic concepts of *feedback loops*, *stocks*, *flows,* and *behavioural modes* required to read any System Dynamic model, are thus provided. Then, a set of alternative simulation approaches are considered, in conjunction with a brief comparison of System Dynamics with exact methods coming from Operational Research. The chapter ends by presenting to the reader relevant academic use-cases of System Dynamics to assess the field of Supply-Chain Management.

4.1. Why do we need simulations

Often decision making is driven by personal beliefs and "gut-feeling" rather than a justifiable set of rules. This became as true as "trivial" the initial query might sound like, triggering the innate human trait of *feeling overconfident about their personal judgments* as poorly as something is known about a subject. A recognized *psychological bias* also known as the *Dunning-Kruger effect*. Such sets of beliefs are called *mental models*, and they are the result of a complex set of causes that change on an individual-basis depending on culture, age, personal experiences, geographic area, wealth status, job role covered and so on.

Simulations are the easiest tool to apply so as to benchmark such mental models and expectations against the hard truth of the complexly routed reality. Surprisingly (to the user), the final answer most likely differs greatly from expectations. For instance, consider folding a 1/10 mm thick A4 sheet in half 40 times. How thick will the final paper block be? And if folding it 100 times? Turns out that most of the respondent judgments extremely underestimated their final answers, being the first case producing a thickness equal to the distance between the Earth and the Moon, whereas folding it 100 times would yield (approximately) the same distance travelled by light in 93 years. This social phenomena emerges all the times the experience gained about an issue is limited and *large repetitions are not available for learning*.



$$W = \pi t 2^{\frac{3}{2}(n-1)}$$

Fig. 4.1. *Folding paper dynamics*

Thus, this is the main role of simulation: provide a methodology to empirically assess hypotheses about a system behaviour, allowing infinite repetitions to support a *feedback learning process* aimed at *triggering a shift in personal perspectives*. Sterman, in its most important piece, "*Business Dynamics. Systemic Thinking for a Complex World*" assess in depth such human behaviours so as to define the proper *analytical mindset* required to modellers when approaching the complex system field. In that piece he also defines simulations as "*management flight simulators*", clearly underpinning the simulation potential in the S&OP context.

As it will be seen in Paragraphs 3.3 and 3.4, a plethora of simulating tools are available to researchers. The uniqueness of System Dynamics (SD) is that it *forces the modeller to abandon the straiglighned decision-making approach, to accept a circular one instead*. Fig. 4.2 shows the two approaches side-by-side.

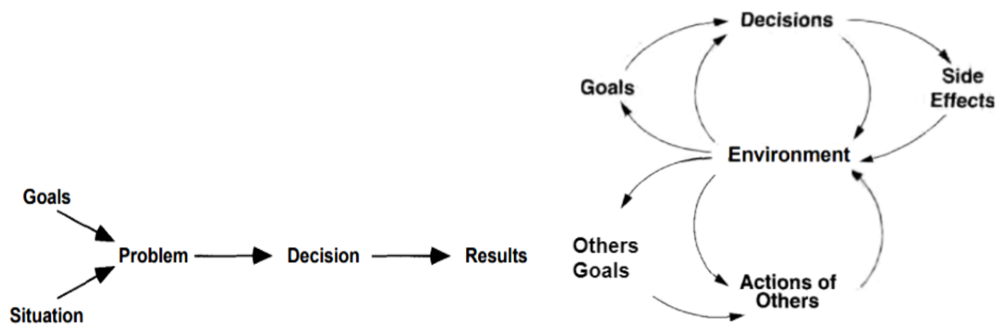


Fig. 4.2. *The Straighlined decision-making approach versus the systemic one.*

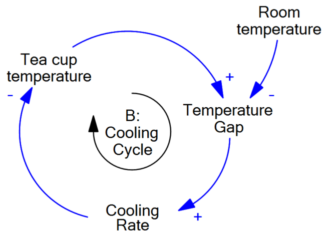
In the straighlined approach, the agents in the system have a certain set of goals to be match as soon as possible, for instance "*reducing inventory excess accumulation in all Cassinetta plants urgently*", and such goals must take place under a certain environment, for instance "*the global COVID19 pandemic mixed with a sudden unavailability of the Suez Canal*". To achieve such goals, an *action plan* is thus developed and *run against the system*, waiting for results to (hopefully) show up. Such an approach is when contingent situations are thrown to the agents living in the system (e.g. Whirlpool GSS management) and required to take a rapid corrective action based on incomplete information. The underlying assumption of the straighlined approach is that *agents' decisions can not influence the future system state*, thus agents are satisfied enough by pursuing a *local optimisation in the short term*. While there is no doubt that pursuing *global optimizations* in some environments, such as supply chains, sounds like a prophetic myth, or sometimes it is even declared impossible by theory, adopting SD force decision makers to add *systemic thinking* to their quick-reaction capability. Finally, being the systems structure circular, their real responses to agent stimuli can be strongly *counter-intuitive* and most of the times unpredictable a priori. This is what the London city government faced while trying to answer the seemingly trivial question of "Should we invest in more and larger roads or more public transport to reduce the city traffic problem in London?". Developing a SD model allowed the governors *to see* that the trivial conclusion of enlarging roads capacity would have produced the expected outcome in the short-run, but let the traffic congestion problem *explode* in the long run. That was due to the simple *reinforcing* dynamics of "larger roads, faster travelling times, more people getting accustomed to the comfort of using the car, thus more people on the roads and the roads getting stuck again, requiring new roads to be built" closing a *self-reinforcing loop*. Such a result was achieved by the father of SD, *Jay W. Forrester*, in one of his most important pieces "*City Dynamics*".

4.2. What is System Dynamics

" The greatest **constant** of modern times is **change**."
Cit. J. D. Sterman

As defined by the *System Dynamics Society*, System Dynamics (SD) is a computer-aided modelling *approach* (rather than a tool) for strategy and policy design, whose main goal is to support informed decision-making when confronted with complex dynamic systems. A system is called *dynamic* when its behaviour is self-dependent, that is, when its state depends upon itself but in the past. This particular feature is mathematically described by differential equations, making the understanding of those systems *complex.*

Looking at nature, dynamic processes can be found everywhere. Consider for instance a hot tea cup seated on a desk at room temperature, its cooling process described by the *thermodynamic laws of natural convection* can be seen as the results of a dynamic process, as shown by the *Causal Loop Diagram* (CLD) presented in Fig. 4.3. CLDs represent sketchy representations of the main model's underlying dynamics where arrows connect variables to describe a *causal relationship between them*. Thus, the Temperature Gap is a cause of the fact that the tea cup and the room are at different temperatures. Next to the arrowhead a positive or negative sign is placed to indicate *the polarity of the relationship.* Positive polarities represent *quantities that move in the same direction*, while the opposite is true from negative polarities. Thus, the Temperature Gap has a positive relationship with the tea cup because if the temperature of the cup gets lower then the lower will also be the Temperature Gap upper-bound. On the other hand, a negative polarity exists between the Temperature Gap and the Room Temperature given that as higher the room temperatures gets, as lower the temperature gap will be.



$$\Delta T(t) = T_{cup}(t) - T_{room}(t)$$

Fig. 4.3. *Natural convection explained by means of a dynamic process*

Being the temperature of the cup at any given moment given by

$$T_{cup}(t) = T_{cup}(t-1) * (1 - cooling\,rate(t))\,;$$

the system's self-dependency is evident. In the SD jargon, such self-dependencies are called *feedback loops* and represent the key to systemic thinking.

The beauty of SD is that while it operates in the field of complex systems, it is not complex as well. Almost surprisingly, all possible emerging dynamics from any possible system are indeed attainable by the interplay of two basic feedbacks loops, namely

1. ***Self-Reinforcing loops,*** where a change in the state of any variable in the loop triggers an everlasting ongoing indefinitely, and

2. ***Goal-seeking loops,*** where a change in the state of any variable in the loop is *penalised* and tried to be pushed back to its initial value.

In other words, self-reinforcing loops tend to "*make things grow (or decay) exponentially*" while goal-seeking loops "*pursue balance and oppose change*". Examples of reinforcing loops might be reproduction, nicotine addiction, fake-news spreading, the Wintel architecture, "defensive" war races and the atomic threat, production quality issues, material fatigue, lost sales from inventory stocks-outs, or global warming, whereas examples of goal-seeking loops might be an arbitrage opportunity in the stock market, the cooling cycles, deaths, market saturation after a new product introduction, the daily inventory consumption, the battery recharging voltage while reaching a full-charge state, or filling a glass of water. To determine the *polarity of a loop*, the polarity of all the causal relationships within it must be assessed. Chained causal relationships transfer polarities following the typical algebraic rules of "plus by plus is plus, plus by minus is minus". Hence if, by following the loop, the overall polarity sign stays fixed after the whole loop has been walked then the loop is a self-reinforcing one, the opposite is true if the sign swaps at the end of the loop walk.

Regardless of the fact that only these two types of feedback are possible, a model might contain thousands of loops interacting with each other. The higher the number of the loops in a model and the longer their average length, the more complex the *system response* is to forecast. The system response is what emerges at the end of the interplay of all those feedback loops together. The resulting *equilibrium state* is reached by the interaction of three basic behavioural modes, namely,

1. ***Exponential growth (decay)***, when the dominant loops is a self-reinforcing one,

2. ***Goal-seeking***, when the dominant loops is a goal-seeking one, and

3. ***Oscillations***, when the dominant loop is goal-seeking one with some *delayed relationship* among some of its variables. In other words, oscillations are generated because during the time required to decide what to do to react to the unwanted change, the system keeps changing in the unwanted direction. When the countermeasure is applied, the system response opposes his direction to a point where it overshoots the target again but from the opposite side. Looped indefinitely this situation generates oscillations.

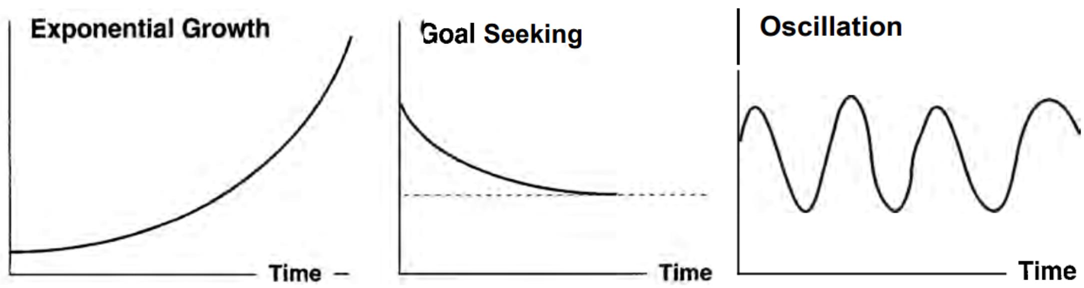


Fig. 4. 4. *The basic behavioural modes of complex systems*

These are the dynamics that would be generated by single loops, but when those get mixed more interesting behavioural modes emerge, namely

1. ***Capacitated growth***, also called "S-shaped growth", underpins the concept of "*nothing can grow or decline forever*". In this situation, both positive and negative loops with no delays exist in the system but an initial exponential growth is dominating, gradually saturating the available *system carrying capacity* up to a point where no more growth is possible. The system carrying capacity is represented by any "global constraint on resources" required by the whole population under assessment. The underlying assumption to S-shaped growth is that the increase in the population does not reduce the system carrying capacity. A typical example of S-shaped growth is city population growth where as soon as the available housing is saturated no more immigration toward the city is possible until new houses get built. This effect is different from a reduction in growth due to an increase of rent rates.

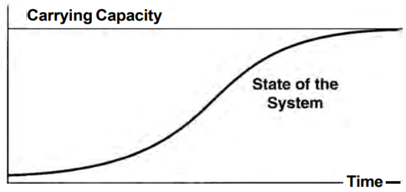


Fig. 4.5. *S-shaped growth*

2. ***Capacitated Growth with Overshoot***, occurs for the same reasons introduced for vanilla S-shaped growth but in this scenario there exists some negative loops having delays among their variables that dominates the picture when the carrying capacity is approached.

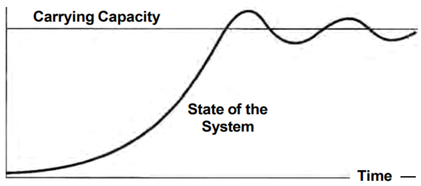


Fig. 4.6. *S-shaped growth with oscillations*

3. ***Capacitated Growth with Collapse***, occurs for the same reasons introduced for vanilla S-shaped growth but in this scenario the assumption of a fixed carrying capacity under population growth is relaxed. Collapse is thus intuitive given that an increasing population erodes an increasing number of resources, up to a point where the rate of creation of new resources is outweighed by the rate of depletion by the population.

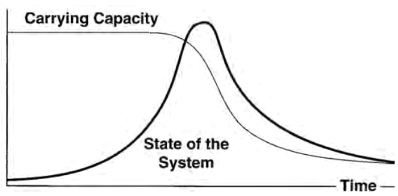


Fig. 4.7. *S-shaped growth with overshoot*

4. ***Equilibrium***, occurs when either the modelled dynamics have no substantial effect on the system state, or when powerful negative loops dominate the picture ensuring the preservation of equilibrium to a fixed *steady state*. While this behavioural mode might seem uninteresting, finding equilibrium conditions for the analysed system might be a non-trivial task. On the other hand, setting the developed model in an

initial equilibrium condition is a mandatory requirement in order to isolate the effect of additional stimuli during the validation phase of the model. From studying the equilibrium properties of the system it might turn out that equilibrium is made of *behavioural patterns,* such as a constantly oscillating response of constant phase and amplitude, or no equilibrium at all is possible.

5. ***Randomness,*** shows up as a proof of the ignorance of the modeller upon some system aspects, hence randomness typically comes from *exogenous variables* included in the model.

6. ***Chaos,*** presents in systems generating dumped irregular fluctuations. Studying chaos implies the adoption of various tools like *phase-plots* and *limit-cycles*. (see Sterman Chapter.2 for a detailed review of *chaos*)

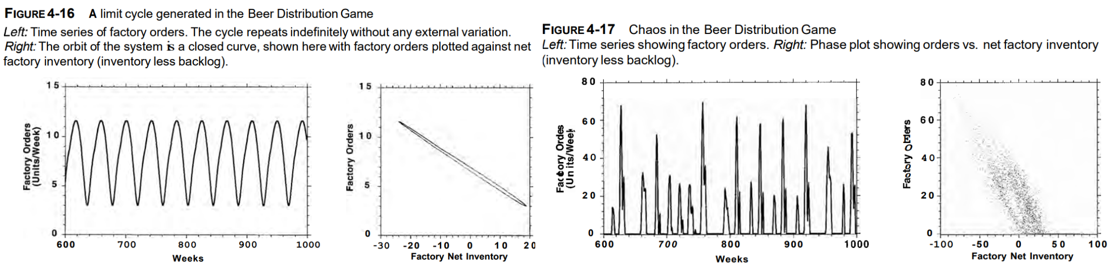


Fig. 4. 8. Chaos analysis in the *Beer Distribution Game*, extracted from Sterman.

Being aware of these behavioural modes gives modellers *the best way to reverse-engineer their models* by looking closely at the studied system response before embarking into the model development phase. For instance, consider Fig. 4.9 where the cumulated Whirlpool inventory trends of the Cassinetta Plants during 2021 divided by product category are shown. Looking at the trends it can be seen that

For refrigeration items, a *growth with collapse behaviour followed by an oscillatory equilibrium* seemed to occur. This analysis suggests that in May 2021, the perpetuated stock accumulation from January saturated some sort of finite system carrying capacity item (e.g. the available storage space) to a point where some of this was lost (e.g. reduction in available vendor willing to accept stock subcontracting agreements), stopping the stock growth to continue, and settling around the new carrying capacity value. Oscillations prove the presence of goal-seeking loops affected by some sort of delay, thus the most plausible hypothesis is that such dynamic is generated by the *attempt to keep inventory to targeted levels in profit plans* but to do so intensive and slow SAP use must be done, delaying the execution of countermeasures.

For cooking items, an *oscillatory behaviour* seemed to occur, plausibly suggesting the same underlying causes found for refrigeration items.
Randomness exists in both ends, capturing the contingent nature of day-by-day situations that might occur during the pursuit of the strategic goals and generate irrational measures to the modeller' mental model.

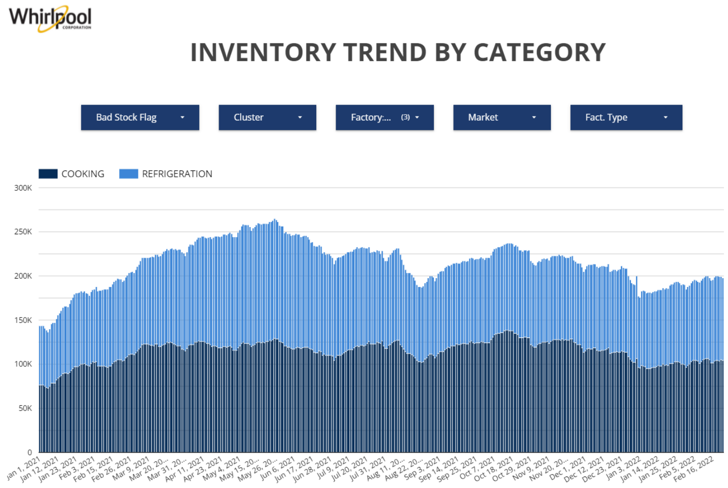


Fig. 4. 9. *The cumulated inventory trends of the Whirlpool Cassinetta plants during 2021.*

The last essential ingredients required to read, understand and, possibly, draw SD models are

1. **Stocks**, represent *accumulations of things flowing in the system*. The concurrent set of all their values at any moment in time is what characterises the *system state*. "Trapping" objects within them, stocks are *the source of disequilibrium in a system*, decoupling the rate of change of flows in the system. Accumulating flows, stocks are mathematically represented by integrals.

$$\text{Stock}(t) = \int_{t_0}^{t} [\text{Inflow}(s) - \text{Outflow}(s)]ds + \text{Stock}(t_0)$$

2. **Flows**, represent *the things that move in the system* and their role is to let the system state move in the continuous system state space.

$$d(\text{Stock})/dt = \text{Inflow}(t) - \text{Outflow}(t)$$

3. **Valves**, represent *flow controllers* regulating the *speed of change in the system*.

wStock, Flows and Valves are the essential components that can not miss in any proper SD model. In addition, some helper variables are available to modellers

4. **Auxiliaries**, quantities re-computed at each timestamp starting from the current state of the system,

5. **Lookup functions,** user-defined *non-linear relationships* among two variables as shown in Fig. 4.10,

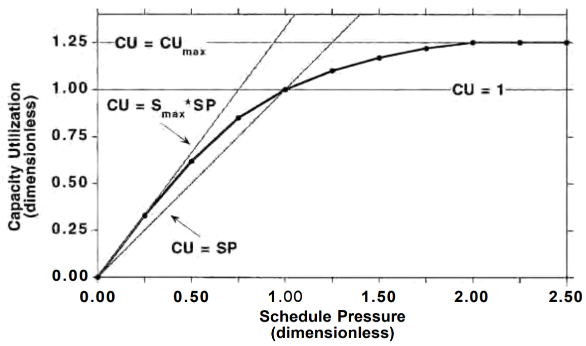


Fig. 4.10. *Table function relating Capacity utilisation and pending orders worklog, Sterman.*

6. **Constants**, immutable values in the simulations.

Fig. 4.11 shows the basic stock-and-flow SD notation and the clear "hydraulic metaphor" characteristic of SD modelling, while Fig. 4.12 shows a full-fledged SD model developed by General Electric to evaluate the effect of leasing durations on the new car launch sales, taking also into account the used-car market dynamics.

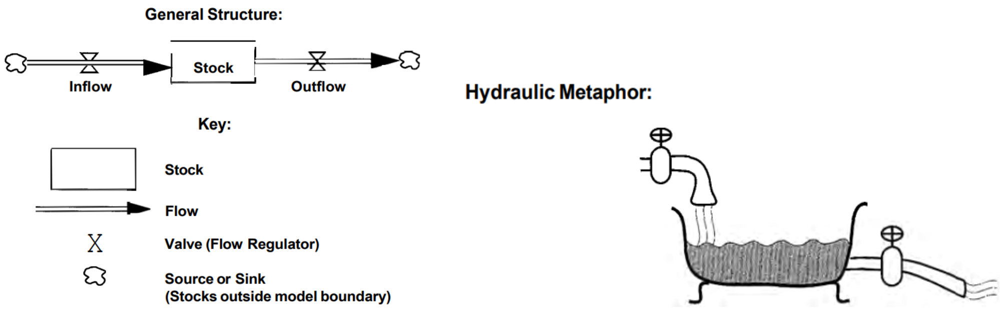


Fig. 4.11. *Stock-and-flow notation developed by Forrester in 1958.*

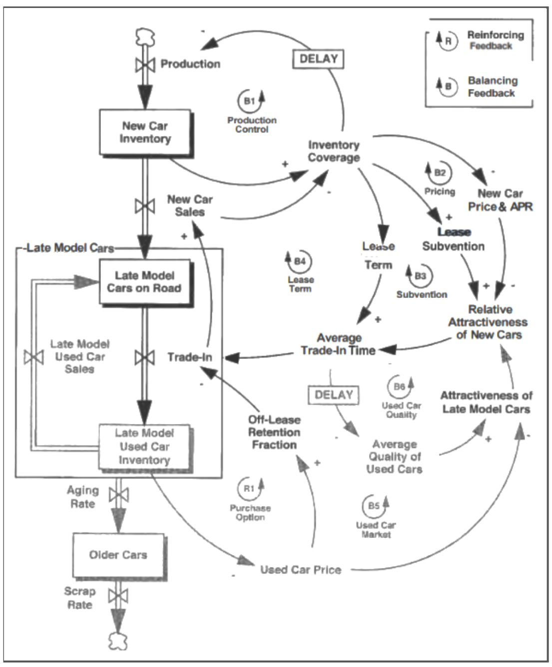


Fig. 4.12. *General Electric SD model to determine the effects of leasing durations on new product introductions*

SD was developed by Jay W. Forrester in the mid-1950's at the Sloan School of Management of Massachusetts Institute of Technology (MIT). The derivation of SD, as many things in engineering, traces back to military applications. Forrester joined the newborn Sloan School of Management in 1956 after a life spent as an Electrical Engineer mostly working on military applications for the U.S. Navy. On this stage, Forrester had his first contact with the simulation field, being the first in devising an aircraft flight simulator to prove the capabilities of the emerging digital computers technology. Such an application brought him fully into the Computer Science field, heading the MIT Digital Computer Laboratory where he released a stream of remarkable innovations that became industry standards, such as the *coincident-current random-access* magnetic computer memory.

Backed by this background and his managerial experience derived from the MIT Labs and many research division held, he concluded that the impassable impediment to progress came mostly from the managerial side of things rather than the engineering one, a direct consequence of the fact that social systems were found much harder to understand and control than physical ones. Forrester's participation at the MIT Sloan School of Management allowed him to study the key success and failure factors of corporations. SD indeed came out during a "serious exercise" held manually by Forrester while consulting for the General Electric (GE) management regarding worrying resignation cycles happening in multiple GE plants every three years. On that stage, Forrester proved, devising a manual *stock-and-flow diagram,* that such events were not driven by GE management beliefs, namely the at the time economic recession, but they were a direct consequence of the latest adopted company hiring policies. From that moment on, it was clear to Forrester that a quantitative approach in studying how human behaviour led to decision making was possible, a bold statement at that time, being the realm of management a strongly qualitative one, driven by uncodified knowledge, senior experience and "gut-feelings". Hence, it could be said that Forrester ideas pioneered Management as a real branch of science.

In the years ahead, Forrester's radical ideas quickly gathered consensus among MIT graduates, leading him to first develop the first SD dedicated programming language called S.I.M.P.L.E. (*Simulation of Industrial Management Problems with Lots of Equations)* in 1958 and DYNAMO in 1959 which became the industry standard in current SD softwares releases.

4.3. System Dynamics against Discrete Event Simulation

SD is not the only tool available for researchers to simulate large complex systems. Indeed, as reported by Tako et al. 2011 in their literature review, Discrete Event Simulations (DES) offer a widely applied alternative to SD, especially for applications of scheduling, resource allocation and capacity planning. In the Supply-Chain Management context, DES applications outweigh SD ones in most of the themes designated by the authors, apart from studies on the Bullwhip effect, suggesting a preference for DES on the operational and tactical themes whereas SD seems more suited for strategic analysis.

The extent to which LSCM issues are addressed by each modelling approach; number of papers (#) and percentage use by modelling approach (%).

	LSCM issues ranked	DES #	DES %	SD #	SD %	HYB #	HYB %
	Supply Chain structure (SCS)	16	6%	2	2%	1	10%
Strategic	Process redesign (BPR)	5	2%	3	3%	1	10%
	Supplier selection (SS)	3	1%	2	2%	0	0%
	Facilities/ Capacity planning (FCP)	5	2%	3	3%	1	10%
	Supply chain integration (SCI)	21	8%	8	8%	1	10%
	Information sharing (ISH)	14	5%	10	10%	0	0%
	Bullwhip effect (BE)	5	2%	18	18%	0	0%
	Reverse logistics (RL)	4	2%	3	3%	0	0%
	Replenishment control policies (RCP)	22	8%	2	2%	1	10%
	Supply chain optimisation (SCO)	21	8%	3	3%	0	0%
	Cost reduction (CR)	10	4%	2	2%	0	0%
	System performance (SP)	28	11%	8	8%	1	10%
	Inventory planning/management (IPM)	47	18%	18	18%	1	10%
Operat/tact	Planning and forecasting demand (PFD)	19	7%	8	8%	0	0%
	Production planning & scheduling (PP-SCH)	27	10%	9	9%	3	30%
	Distribution and transportation planning(DTP)	14	5%	1	1%	0	0%
	Dispatching Rules (DR)	4	2%	0	0%	0	0%
	Total	265	100%	100	100%	10	100%

Fig. 4.13. *Comparison results between DES and SD uses in SCM, extracted from Tako et. al 2011*

Being both simulation tools, they both share a panel of features and few essential differences. Being the author non-familiar with DES is out of the scope of this section to declare a winner among the twos but just to present the available alternatives. From Tako, what seems a promising approach is a hybridisation of the two methods so as to achieve higher performances.

As intuitable by its name, DES atomises the system response in a discrete sequence of events (and not timestamps). The whole simulation is just basically a schedule of all events happening throughout time, which is merely a variable used to order such events occurrences. The list of possible events is provided by the modeller and scheduled to occur at any moment upon stochastic use of probability distributions. Events occur when, upon the extraction of pseudo-random variables from those distributions, the relative cumulative probability is higher of a certain threshold. Occurrence of an event might trigger a cascaded *priority queue* of chained events. The occurrence of an event lets the system state change permanently. The state of the system is determined by the set of values of the attributes assigned to the model *entities*. Multiple events can happen concurrently at the same time.

The discrete nature of DES entails the biggest difference with SD. In DES, simulation *time is a cause* of event occurrences. No changes to the system state are possible in the transition phase between two "moments" of the simulation.

In SD the effects of an emerging dynamic might virtually spread among all timestamps in a continuous way, being the approximation logic based on a "continuous" time integration assumption of its variables. Continuity is given by a constant quantisation of time as required by the modeller.

Being brief, reproducing with high fidelity a weather forecasting model taking temperature changes into consideration is not reproducible by DES, while it is in SD. On the other hand, a model of a waiting queue at a postal office is reproducible with high fidelity in DES, but also in SD. However, it must be acknowledged that in such a case the heavier computational requirements needed to perform a continuous integration are somehow wasteful because they will not yield an enhanced final answer.

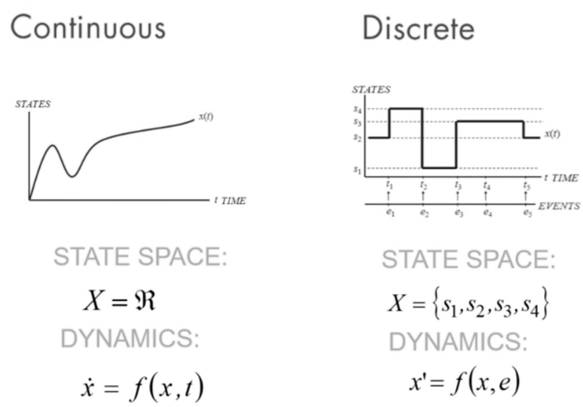


Fig. 4.14. *DES integration approach against SD one.*

Every DES model can be represented by the combinations of the followings:

1. ***Servers***, the equivalent of stocks in SD. They keep entities in place for a certain period of time;

2. ***Gates***, the equivalent of valves in SD. They let entities move along the system;

3. ***Entities***, representing single objects moving in the system. In SD there is no need to refer to specific object instances rather similar objects are grouped in the same flows;

4. ***Queues***, similar to delays in SD. Entities stationate in the queue for an undetermined period of time.

On the other hand, in SD everything is modelled only as a set of stock and flows. Fig. 4.15 presents a simple DES model representing the passenger boarding dynamics of an aircraft. Passengers are the Entities while the corridor is the Queue. At each seat row, one passenger at the time can take a left or right seat. This is represented by a Server of unitary capacity. Once seated, entities leave the system, thus seats represent Exiting Gates.

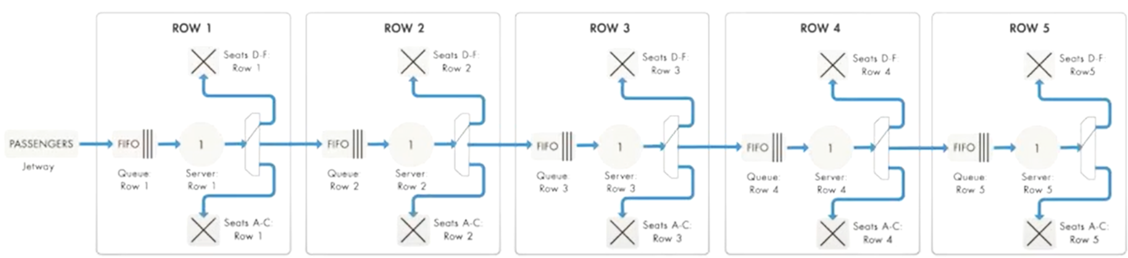


Fig. 4.15. *A DES model representing passengers boarding on a flight*

Finally, DES solutions are supported by tools commonly used by researchers in the SCM field, like MatLab, something instead missing for SD which instead requires the use of proprietary softwares (e.g. Vensim).

4.4. System Dynamics against Operational Research

On the other side of the spectrum, simulations are opposed to exact methods and operational research methods in general, belonging more to the *realm of heuristics*. The typical aim of both is to determine a set of values for the problem input variables so as to maximise or minimise an objective function (e.g. a cost function to minimised, a profit function to be maximised),

Exact methods differ from heuristics because of their mathematical provability of yielding the best solution possible for the tackled problem, thus also called *optimal solution*. However, a big downside of exact methods is that they escalate in solving complexity as large as the number of the variables in the system gets, rapidly leading to the famous category of *Nondeterministic Polynomial* (NP) and NP-hard problems. For those no deterministic polynomial algorithm is known able to solve them in a bounded time, typically requiring deploying logarithmic or exponential complex algorithms to solve them. All these translate from long computational times to non-solvable problems at all. Fig. 4.16 shows how the solving time complexity, also denoted by the big-O notation O(f(n)), grows as the input size grows.

		size n					
	Type of function	10	20	30	40	50	60
polynomial	n	0.00001 seconds	0.00002 seconds	0.00003 seconds	0.00004 seconds	0.00005 seconds	0.00006 seconds
	n^2	0.0001 seconds	0.0004 seconds	0.0009 seconds	0.0016 seconds	0.0025 seconds	0.0036 seconds
	n^3	0.001 seconds	0.008 seconds	0.027 seconds	0.064 seconds	0.125 seconds	0.216 seconds
	n^5	0.1 seconds	3.2 seconds	24.3 seconds	1.7 minutes	5.2 minutes	13.0 minutes
non pol	2^n	0.001 seconds	1 second	17.9 minutes	12.7 days	35.7 years	366 centuries
	3^n	0.059 seconds	58 minutes	6.5 years	3855 centuries	$2x10^8$ centuries	$1.3x10^{12}$ centuries

Fig. 4.16. *Solving complexity growth of different algorithms classes, extracted from Della Croce, 2021.*

The biggest advantage of heuristics is thus their faster solving speed coupled to a "good enough" precision. Their performances are given by the different approaches followed to tackle the problem. While exact methods seek for exact mathematical formulations to produce the optimal solution, heuristics instead try to brute-force it by guessing all possible combinations of the inputs and later checking the final objective value reached under the problem constraints. The more cleverly the guessing game is held, the faster and the more accurately the heuristic *converges* to the optimal value. This versatility led researchers to devise a plethora of heuristics exploiting different strategies to explore the *solution space of the problem*, sometimes also by getting inspired to physical thermodynamic concepts as in the case of Simulated Annealing. In Simulated Annealing the search strategy is constructed on the concept of "minimum energy state" and "temperature" of the system. A higher temperature equals a higher entropy of the system, letting the heuristics behave more frenetically in the exploration of the space and moving around following a *random walk logic*. When the temperature settles down a *steepest descent walk* is followed instead. By devising temperature profiles resembling the "annealing cycles" used in metals manufacturing processes, the solution space can be explored without getting stuck in a *local optimum*. A promising trend is brought in the field of operational research by the introduction of *matheuristics*, namely heuristics exploiting exact methods to construct their solution space exploration rule.

For the reason given above, exact methods seem applied more frequently to problems pertaining to the operative or tactical level, delegating broader scenarios to other methods among which simulations are a first choice. Finally, as evidenced by Simchi-Levi, Chapt. 2, being exact methods most of the time ran against aggregated and imprecise input data, in the decision maker perspective their cost in providing an exact solution to an approximated problem is typically higher than relying on an good-enough approximate solution to an approximate problem that converges much faster and thus can be rerun multiple times.

APPLICATIONS AND ANALYTICAL TOOLS

Problem	Tools used
Marketing	Query, statistics, data mining
Routing	Heuristics, exact algorithms
Production scheduling	Simulation, heuristics, dispatch rules
Logistics network configuration	Simulation, heuristics, exact algorithms
Mode selection	Heuristics, exact algorithms

Fig. 4.17. *List of suggested tools to use for different problems categories in SCM, extracted from Simchi-Levi.*

4.5. Existing SD applications to Supply Chain Problems

Sterman's contribution in his famous "*Business Dynamics*" represents today's biggest SD body-of-knowledge. In that piece a broad span of themes is touched, ranging from pandemic spreads to supply-chain management, thus showing the extreme flexibility of SD as a tool for exploring different fields following an empirical approach. As it will be seen in Chapter 4, extensive references are done in this study to Sterman, Chapter 16-17-18 so as to recreate the base underlying structure of the proposed SD model.

In academic literature, SD seems heavily used to address topics pertaining to "holistic issues", thus themes of diffusion of innovation, governmental policies effects or Bullwhip-reducing cooperation strategies in supply-chains emerge. Following, a panel of recent academic uses of SD pertaining supply-chains considered highly relevant during the development of this study are introduced.

1. *Dominguez, Cannella, Ponte, Framinan*, 2021, explore the effects of information sharing among subsets of agents in a multi-echelon supply-chain when the majority of the agents do not collaborate instead. The developed SD model allows the author to benchmark seven different information-sharing scenarios, drawing managerial recommendations for decentralised supply-chain contexts.

Mangano, Zenezini, Cagliano, DeMarco, 2019, develop a SD model to quantify the efficiency gains induced by the diffusion of ICT innovative platforms in the context of city logistic operators and last-mile deliveries.

W.S. Chang, Y.T. Lin, 2018, developed a SD model to assess supply-chain resilience to disruption induced by extreme variation in Lead Times in a multi-echelon context made a factory, a distributor and a retailer. The authors exploit their model response to devise two effective mitigation strategies.

A. Perugini, A. C. Cagliano, 2018, develops a SD model to review the internal logistic dynamics of the Loccioni Group. In this study the model is exploited by the author to underpin inefficiencies in the current picking processes involved in a typical Engineering-to-Market Loccioni's customer order. The study concludes by illustrating improvement proposals based upon the model response to Loccioni's historical data.

M. Postorino, A. De Marco, 2018, after a visiting period at the College of Technology Innovation of Zayed University of Dubai, the author develops in his master thesis a SD model to identify investment opportunities that could lead to an increase in the TEU capacity of the Dubai logistic corridor project.

A. C. Cagliano, Carlin, Mangano, Rafele, 2016, pursue an investigation about the key drivers of the diffusion dynamics for Full Electric and Hybrid vehicles adoption by third-party logistics service providers (LSP) in the context of parcel deliveries in the city of Turin, Italy. A SD model utilising the Bass diffusion model as diffusion engine is devices with the aim of understanding how effective the spreading mechanism of word-of-month, advertisement, public concern about sustainability and public incentives are in driving the shift to greener logistics.

Langroodi, Amiri, 2016, developed a SD model representation of a multi-echelon, multi-product, multi-region supply-chain made of five main cascading actors, namely retailers, final product distributors , manufacturers, material distributors, and suppliers, spread in four regions. The aim of the modellers was to determine which region should be entitled to rule the others so as to minimise the Bullwhip effect under a stochastic demand input.

As it emerged above, differently from Operative Research and Optimisation, SD seems capable of moving nimbly between operational, tactical and strategic contexts. Exact provability remains the only downside of SD with respect to optimisation-based approaches. On the other hand, SD biggest advantage is that most of the times managers hardly base their decision making on exact but rigid optimisation results, rather they privilege agile "roughly-right" heuristics that can be re-run quickly against new emerging environment condition

Chapter 5

The Proposed Model

*" The **eye** only sees what the **mind** is prepared to **comprehend**. "*
Cit. Henri Bergson

There is no point in creating a model that should be trusted "blindly" on the modeller's words, hence in this chapter the proposed SD model is fully disclosed to the reader by decomposing it to its individual parts. Starting from the plain explanation of the author's dynamic hypothesis about DDMRP, the focus shifts on its effective development organised in three separated waves. To close each wave, the constructed hypothesis is tested for impairment by applying multiple validation strategies against it, such as historical data fitting, extreme test condition and univariate sensitivity analysis. In this chapter all the knowledge collected throughout the previous chapters is pulled together by the desire of being mature enough so as to understand it, making not an exact model of reality but an open window about it.

5.1. Model boundaries and the initial causal loop diagram

To apply System Dynamics effectively is mandatory to have a clear idea of what the purpose of the model is. On the other hand, particularly for non-expert modellers as the author, the typical problem at the beginning is not where to start but where to cut it. The simplicity of the System Dynamics tools for modelling somehow allows adding causal relationships between variables virtually for free, giving the impression to rookie modellers to be building a very sophisticated model.

As anticipated in Chapter 3, *Causal Loop Diagrams* (CLD) are the first tool provided by System Dynamics theory to tackle this issue and force the modeller to lay down the underlying *dynamic hypothesis* of the study - thus confirming if there actually exists one - so as to later benchmark it against the insights revealed by the agents living the real system. Most of the CLD cannot be considered enough to build a complete SD model, being this task rather performed by developing *stock and flows* diagrams. On the other hand, CLDs are usually complex enough to map the key causal relationships and feedback loops that will be captured by the flagship model, and act as "readable documentation" about the model boundaries.

For those reasons, developing a CLD for the case study was the first milestone to reach. The initial CLD was developed trying to summarise the knowledge gained during the 6-months internship period in the company procurement office, and it is presented in Fig. 5.1.

Is trivial to see the messiness included by the author in this chart, fiercely trying to build "the model of everything". As mentioned before, this instead reveals a certain lack of focus on the scope of the SD model. While this was also clear to the author at the time, it is worth mentioning that this step took place when no further reading about SD was done, nor any idea introduced in Sterman, Chapter. 16, about the *stock management problem* were considered. On the other hand, keeping this CLD was considered of key importance in order to fix a clear picture of what was the initial author's mental model about the real system before deep diving with the analysis, and be sure that any possible personal bias would not be included in the flagship model.

The main causal loops are highlighted in the chart by different colourings. For the ones considered the most impacting, a descriptive name is given and the loop polarity is determined. This activity let an initial bias emerge: only 2 reinforcing loops are contrasted by 7 balancing ones, somehow biassing the system response to a general decay. Finally, variables coloured in pink represent *exogenous variables*, thus their dynamics are not studied.

To effectively read the chart, it is suggested starting from its "core loop" B1, highlighted in blue, in the centre. Indeed, all "dynamics" are builded on top of the "*Daily Consumption*" balancing loop which characterise the interaction between the daily demand for goods and the on-hand inventory. Every day, the daily demand is compared with the actual inventory on-hand, defining the satisfiable portion of demand. This quantity is withdrawn from the inventory in the form of daily shipments, closing a balancing loop. It is a balancing loop given that an increased quantity of available stock allows more daily shipments, thus higher inventory withdrawals and so a reduced inventory to start with in the next iteration.

The picking operations performed by B1 trigger the "*Buffer Replenishment*" balancing loop B2, highlighted in light blue. The goal of B2 is to prevent the inventory to stock-out, issuing an higher replenishment order to the upstream productive nodes as lower as the daily inventory position is, thus closing a balancing loop.

It is typical of many industries that the unsatisfied portion of daily demand is not immediately lost, rather this quota of orders gets accumulated in what is usually referred to as "*orders on-allocation*". This situation usually occurs either when:

1. **there are strategic customers** to whom a percentage of the productive capacity must be always assured thus other minority customer orders get intentionally delayed, or

2. **new product launches are announced**, so orders get prioritised in order to prevent inventory stock-outs during the production ramp-up stage, or

3. **inventory cannot actually satisfy demand**.

Obviously, customers that see their orders being put on-allocation are willing to wait up to a certain amount of time before deciding to withdraw their order and seek for alternative procurement. This time-lag is conventionally known as the "*Customer Tolerance Time*" (CTT) and is usually aggregated as the average - or the minimum - CTT of each customer.

There are many ways in which orders on-allocation can be prioritised, in the proposed model the FIFO logic is applied instead mainly due to its simplicity in modelling in SD. Moreover, the FIFO approach allows the introduction of CTT in the explanation of the company order fulfilment process.

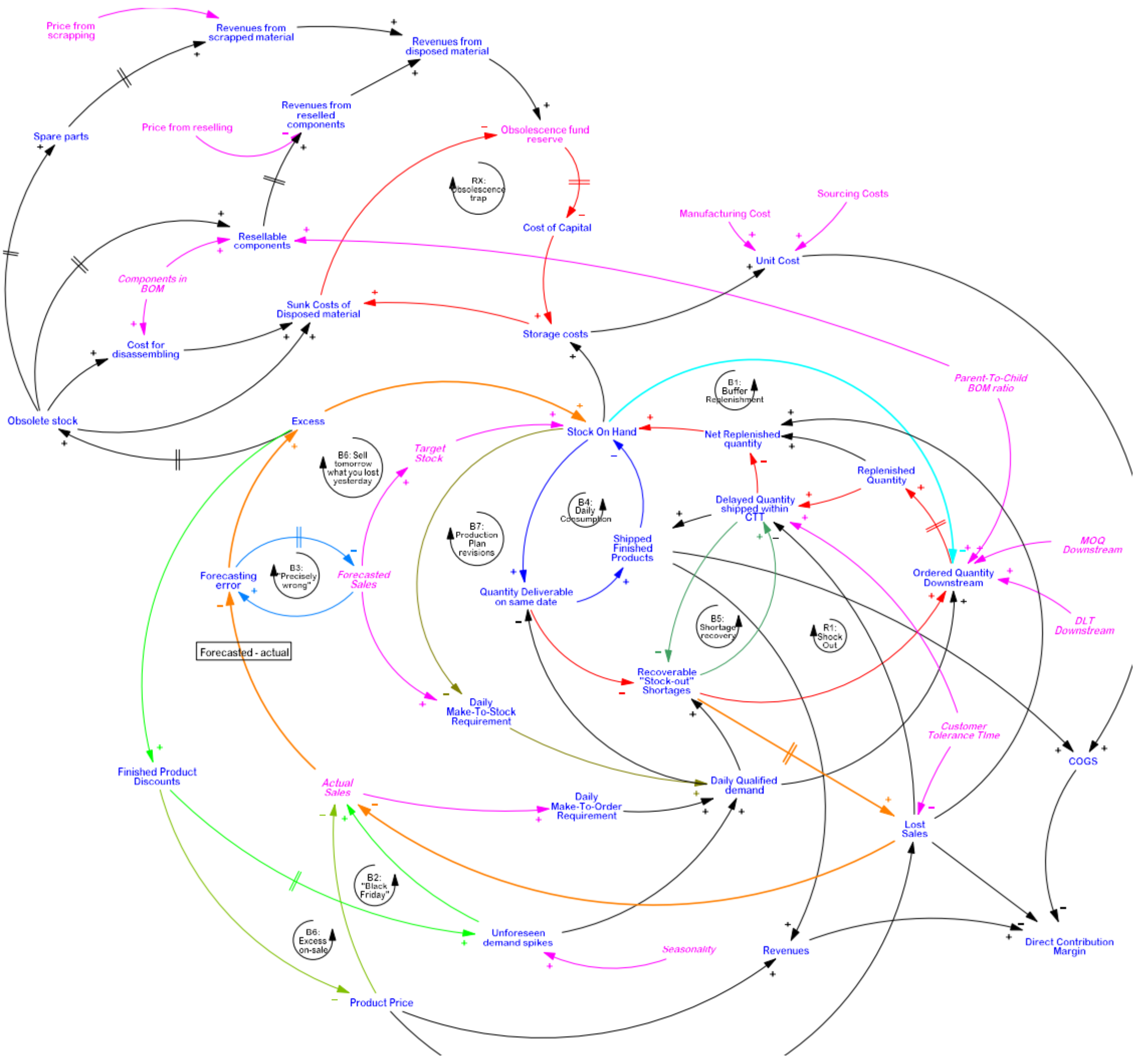


Fig.5.1. *The initial Causal Loop Diagram*

The "*Stock-out*" reinforcing loop R1 and the *"Shortage Recovery"* balancing loop B3 try to grasp the dynamics explained above. Those loops are intertwined and can be considered as two sides of the same coin. Indeed, the goal of B3 is to reduce the order on-allocation backlog, immediately withdrawing the maximum available amounts from the incoming replenished quantities in order to fulfil within CTT all the back-orders, thus preserving a high customer satisfaction, and closing a balancing loop. On the other hand, reducing the net replenished inflow of goods to the inventory also reduces the available quantities to fulfil new demand, generating more orders on allocation, closing a reinforcing loop instead. The interplay of R1 and B3 produces the sort of effect of a "*cat chasing its tail*", where the company (the cat) trying to fulfil backorders (the tail) as soon as possible also reduces the daily service levels, generating new orders on-allocation. Thus an interesting trade-off between service levels and customer satisfaction is generated by the dominance of any of two loops.

Being the assessment of what happened in Cassinetta during the 2021 spring (see Chapter 2) the fil-rouge of this study, a modelling effort was spent in order to assess the possible dynamics generating inventory excesses and high obsolescence risk.

In the initial CLD the excesses are considered generated mainly by an error in the forecasts. The dynamics generating the forecasting error are considered influenced only by 2 drivers:

1. The *actual difference between actual sales and forecasted sales*, revealed only at each new iteration of the simulation, and

2. The *too delayed production response* to backorders.

While the first driver is quite self-explanatory, the second one requires a bit of abstraction. When unsatisfied demand gets accumulated in the orders on-allocation backlog, a count-down dictated by the CTT starts. If the productive environment is not capable of pushing enough goods with a shorter-than-CTT lead time, those orders will be lost. If this situation occurs, most probably the production of those expedited requests has already started and they are currently developing along the line. Once orders for those quantities get cancelled, by all means those represent not-anymore-needed units, or in other words, excesses.

Such dynamics try to be cathed by the interplay of the "*Precisely Wrong"* balancing loop B4 and the *"Excess ready for tomorrow sales"* balancing loop B5. Considering all the above, the fact that those dynamics should emerge by the interaction of two balancing loops can be considered as a weakness of the model. On the other hand, loop B5 is a natural consequence of the second driver. Consider for example that the forecasts are 100% correct, thus the only source of mismatches between forecasted demand and actual sales are the cancelled orders due to a slow productive response. If forecasts stay accurate, the excess produced in the past is not dismantled instantly but can be actually exploited to promptly satisfy demand, thus reducing new shortage creation and, thus, the chances to produce additional excess due to slow production. Finally, as was reported by multiple GSS analysts, in some scenarios :

- *"producing something sometimes is better than producing nothing "*,

- *" there are costs associated with an empty production line "*,

- *"some high-runners are produced even without a specific demand "*.

Is not a novelty that high-volume production environments such as flow-shops prefer mostly stable schedule plans and throughput rather than "starts-and-stops". Thus, excess generation might also be explained as the result of the process of trying to couple a constant supply signal to a fluctuating demand one. Additional underlying dynamics explaining the excess generation are thus hypothesised. In addition to B5, other 2 additional "excess absorption" mechanisms were identified:

1. **Sales discounts** (loops B6 and B7), and
2. **Goods obsolescence**.

Described in the top section of the CLD, obsolescence dynamics were mainly assessed from a financial perspective. The key metric considered for obsolescence was the portion of the obsolescence fund left available after each iteration. The obsolescence fund represents a financial reserve that Whirlpool instantiates yearly - along with the profit plant - and is used to discount obsolescence-related losses. Practically, it is used as a benchmark metric to understand how rapidly obsolescence material grows in which plant and compresses profits. After a 12-months delay with no good movements (see above), materials are considered obsolete. Being the CLD focused on finished goods, obsolete units can either flow out of the system as *"spare parts"* or *"resellable components"*. Thus, for each obsolete unit, the total cost for storage and disassembly is accrued as *"sunk costs of disposed materials"*. Disassembling costs are considered sunk because they are "incurred twice" given that previous costs were incurred to assemble the finished product together. These costs are netted with the total gains from scrapped material and components resellings revenues, so as to establish the net decrease (or very unlikely increase) of the remaining available fund. The obsolescence section holds at its core the second reinforcing loop of the model R2, *"The obsolescence trap"*. It is a reinforcing loop given that a decrease of the available fund after some time obliges the acquisition of additional capital to offset losses, thus increasing the overall company weighted average costs of capital (WACC) in the long run. An increase in WACC leads to an increase also in the costs attributed for future obsolete material, thus further reducing the obsolescence fund even quickier.

To conclude, to understand the overall interplay of all the presented dynamics in a single metric, the final aim of the modeller was to let all loops have an impact on the final DCM of each SKU.

5.2. Policy Structure Diagram

Fig.5.2 presents an high-order representation, also known as *policy structure diagram,* of the final proposed SD model, highlighting the basic interaction between its six sub-models and the most relevant KPIs generated by them.

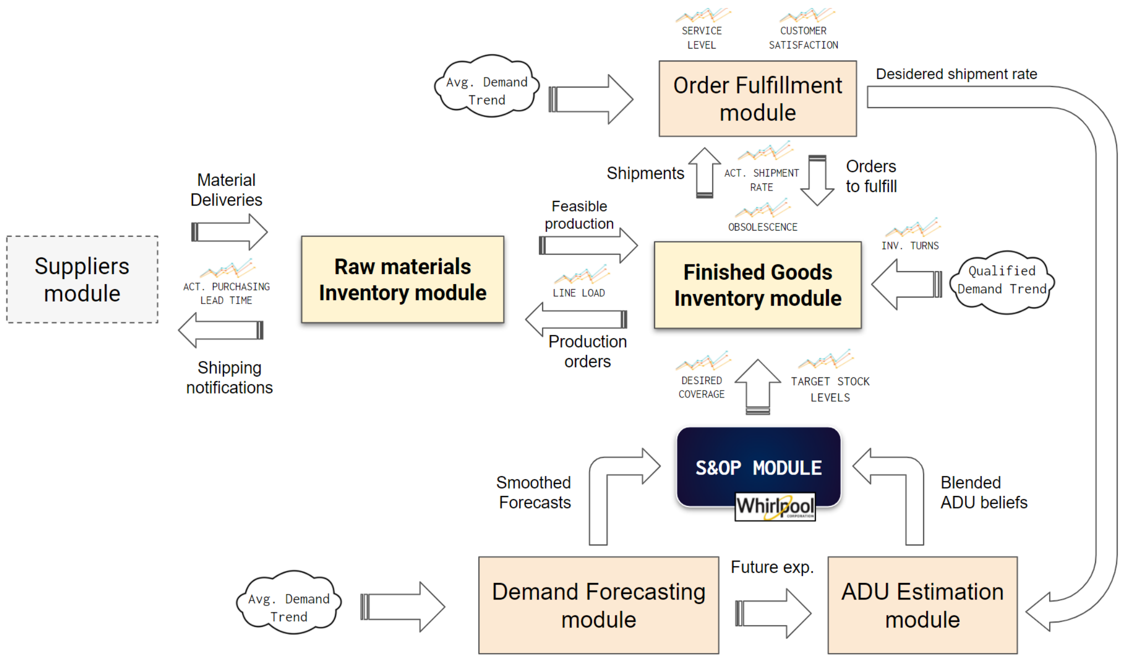


Fig. 5.2. *Policy structure diagram of the proposed SD model*

The choice of a modular approach was pursued in order to keep the model

1. **as simple to understand** as possible, thus allowing future modellers to quickly step into it (e.g. Whirlpool employees),
2. **easily manageable**, and
3. eventually, **scalable**.

All modules play a pivotal role, but, as to speak, the *essential* modules are the one dedicated to material inventory dynamics, colored in light yellow.

The **Finished Goods Inventory Module** encloses all dynamics related to goods production, finished good inventory management and warehousing. To do so, it must interact with the **Raw Materials Inventory Module** where all dynamics related to raw materials inventory management are modelled instead. The interaction between them is established through *Production Orders*, released by the Finished Goods Inventory module while engaging into the Buffer Replenishment Loop B1 to restore the *Target Inventory* threshold. The Raw Materials Module responds by only releasing the *Feasible Production with Raw Materials on Hand*, acting basically as a potential bottleneck for upstream replenishment. The effective released production saturates a portion of the flow-shop capacity, defining the *Line Load*. Released production remains stationary by means of a MATERIAL DELAY for a fixed period of time, namely the *Manufacturing Lead Time,* before moving into the finished good inventory stock.

The **Suppliers Module** reproduces the supply base *as a single entity* which, upon receipt of a *Purchase Order* (e.g. Open Schedule Lines) from the Raw Materials Module, releases material after a fixed time-delay, namely the *Agreed Purchasing Lead Time*. In contrast with what is done in Sterman, the Suppliers Module is a rather simplistic one. This approach was reasonable given that Whirlpool obviously have no visibility about its suppliers data (even for the co-located supplier in Cassinetta) apart from the Purchasing Agreements and the Open Schedule Lines, thus it was preferred to avoid modelling something unknown rather than embarking into a guessing game about the suppliers dynamics, running the likely risk of just introducing noise in the final model response and making its validation trickier. Very simple logics for modelling *Material Delivery Delays* are included by adding randomness to the initial *Agreed Purchasing Lead-Time.*

The remaining modules are defined as *supporting modules,* even if they have the potential to drive the whole model dynamics.

The **ADU Estimation Module** represents one of the main DDMRP customization build upon the Sterman base model, re-applying the *agent's expectation creation theory* concepts introduced in Sterman, Chapt. 10, so as to simulate the ADU estimation process typical of DDMRP. Its role in the model is to generate the *blended ADU expectation trends*, exploiting both past and future desired consumption trends. Past desired consumptions are collected from the **Order Fulfilment Module**, where backorders and daily new orders are aggregated so as to determine the daily *Desired Shipment Rate*, that is the rate at which the manager of the system would like to pick-pack and ship goods from inventory, assuming an infinite availability of goods. In other words, the *Desired Shipment Rate* represents the shipment rate which would always guarantee a unitary *service level* and *fill ratio.* The discrepancies between the *Desired Shipment Rate* and the current *Finished Goods Inventory* determines the *Daily Fill Ratio*. Unsatisfiable orders accumulate among the *Orders On-Allocation*, waiting to be either fulfilled or cancelled. The ratio between the cancelled orders at each timestamp and the total orders received with CTT determines the *Customer Satisfaction*.Past ADU consumption trends are then evaluated by averaging the *Desidered Shipments Rate* requested during the previous 6-weeks.

Future consumptions are evaluated through an averaged linear projection of the *rate of change in expected customer orders*. Such rate is nothing more than the difference, at each simulation timestep, between the new actual demand and the previous manager's expectation about it. All those metrics are produced by the **Demand Forecasting Module**, where the well-known process of *exponential smoothing of forecasts* is performed. Both the Demand Forecasting Module and the Order Fulfilment Module are mostly re-creations of the base models presented in the Sterman, with little additions to let them to also take into account of, respectively, a second input demand trend, namely the *Qualified Demand* necessary to implement DDMRP, and the *order cancellations* logic.

Finally, in the **S&OP module**. Based on forecasts and ADU trends, the target inventory levels are set accordingly to the following basic approaches.

1. ***Reorder-point logic***. The manager sets the target inventory levels so as to maintain a fixed amount of “days of coverage”, based on her expectation about future customers

orders. Replenishment orders are generated taking full consideration of the state of the supply-line (see Sterman Chapter 16) and the expected customer orders.

2. ***DDMRP logic***. The manager sets the target inventory levels as introduced by DDMRP theory (see DDMRP Optimal Inventory Range in Chapter 2), based only on her estimates about the ADU trends. Replenishment Orders are generated using the Net Flow Equation, thus taking full consideration of the state of the supply-line.

The S&OP module represents the *corporate operative strategy development*, where management can actually decide which inventory policy to apply to manage inventories and benchmark financials.

The proposed model can be against a desired number year assuming *daily buckets* as the minimal time units. Therefore, all model's parameters and inputs must be provided on a daily-basis.

5.3. Model development

“ ***All*** *models are* ***wrong****, but some are* ***useful*** ”
Cit. George E. P. Box

The CLD in Fig. 5.1 was reviewed multiple times with GSS analysts and the academic tutor, deciding what to include and what to cut. The development plan would have followed ***three waves*** where expansions to the model boundaries would have been done gradually after passing a validation phase.

During the *first development wave* (W-I), the focus would have been on **modelling general material movement dynamics from raw materials to finished goods**, discarding any excess, shortage or obsolescence generation logic. Moreover, all financial metrics were also paused. During this wave, the *Sterman manufacturing company model template* would have been used to constitute the model backbone. Validation for this phase would have required the model to reproduce the same behaviour shown in Sterman.

During the *second development wave* (W-II), o**bsolescence generation, productive capacity saturation and order cancellations dynamics would be added**. Validation of this phase would have required all modified stocks not to violate the basic physical law of mass conservation, thus falling below zero unexpectedly. From these additions the Daily Service Level and the Customer Satisfaction KPIs would be computed. Obsolescence would be evaluated by the total obsolete material trends and the accrued obsolescence risk.

During the *last third development wave* (W-III), **DDMRP customisation would be added on top of the Sterman base model**, modifying it as little as possible so as to not substantially change its known behaviour. This would allow an easier interpretation of the new model response. Finally, *an initial connection with financial metrics would be done,* computing average inventory levels, turnovers and days of stock. Validation of this phase would have been carried out by benchmarking the model against known and largely published DDMRP simulation datasets first. Following, an extensive validation phase based solely on the Whirlpool real inventory dataset would be carried out. This, as one can imagine, represents the most delicate part of the study, where substantial discrepancies with historical trends would mean "a blinded investigation in understanding why". On the other hand, only divergences create opportunities to improve the model, to a point hopefully where a higher understanding about the real one is reached.

Finally, both model development and its validation and sensitivity analysis were performed by using the Vensim® PLE Plus software package.

As a legend for the reader, in the following paragraphs the following drawing conventions applies

- *white boxes* identify ***Stocks***,
- *red pipes* identity ***Flows***,
- *blue arrows* identify ***Causal relationships among the model variables***,
- *orange hexagons* identify ***Simulation scenarios***,
- *light blue boxes* identify ***Table function*****s**,
- *yellow circles* identify ***KPIs***,
- *dashed black arrows* identify ***input variables for KPIs computing***,
- *pink text and arrows* identify ***Exogenous variables and their effect on the system***,
- *grey arrows* identify ***initialization conditions***.

Details about the initialisation condition necessary to set the DDMRP configuration in an equilibrium state are given in Par. 5.3.5.6.

5.3.1. Wave I : Reproducing the Sterman base model

5.3.1.1. Finished Goods Inventory module

Fig. 5.3 introduces the base Sterman model dedicated to the finished goods inventory dynamics, duplicated in the presented model with some slight changes to match it with the study aims. The main changes applied concerns the fact that the proposed model, as opposed to Sterman ones, is not grouping multiple finished goods in the same stock. In addition, the minimum time targeted for fulfilling incoming orders is assumed unitary. Thus, in opposition to Sterman, all the inventory on-hand and the daily throughput can be picked in a single day. Following the panel of variables included in this section is introduced.

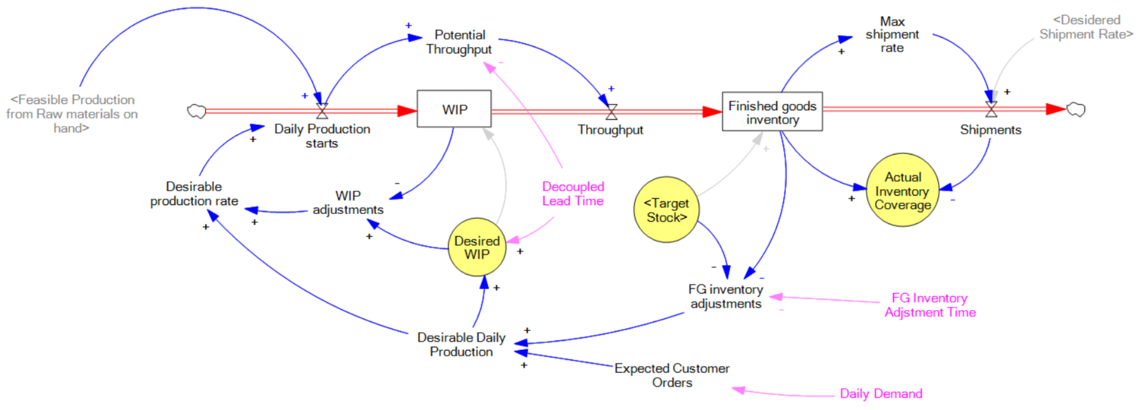


Fig.5.3. *Stock and Flow diagram of the base Finished Good Inventory Module*

Daily Production Starts. Identifies the size of the daily production order released to the productive system. It can be seen as a "production kanban". Its value is constrained by either by the maximum production realisable by curren raw materials reserves or by the required amount needed to keep the finished good inventory to the targeted amount.

```
Context = Endogenous          Type = Flow       UOM = units/day

Daily Production Starts =
  INTEGER
   (
    MIN
     (
          Feasible Production from Raw materials on hand,
          MAX(Desired production rate, 0)
     )
   )
```

In the ideal case, thus when an infinite availability of raw materials is coupled to an uncapacitated productive environment, the manager of the system would be free to release the production order that optimises the future state of the finished good inventory, namely the *Desidered Production Rate*. Hence, the fuzzy MIN function is utilised to implement this logic, always selecting the Desired Production Rate if the amounts of raw materials available allows even larger production, or constraining it to a complete withdrawal of raw materials in the opposite case. Finally, the Desired Production Rate during periods of excess accumulation might turn out to be negative. That is, the manager would like to get rid of some of the available quantities. However, the Desidered Production Rate is bound to be non-negative, being impossible to let the productive system absorb existing units. Rather this task might be achieved by introducing finished goods scrapping dynamics generated by their obsolescence (see Par. 5.3.3.1.3). Finally, quantities are constrained to be finite by the INTEGER function.

Feasible Production from Raw materials on hand. Being defined by variables pertaining to the Raw Materials Module, its formulation and description is detailed in Par. 5.3.1.2.

Desired Production Rate. The desidered production rate after the manager has fully considered the current status of the Finished Goods Inventory *supply line*, namely the WIP stock.

```
Context = Endogenous          Type = Auxiliary Variable          UOM
= units/day

Desired Production Rate =
INTEGER(Desired Replenishment Production + WIP adjustments)
```

The supply line is a central aspect of the *stock management problem* introduced in Sterman. Briefly, managers can decide whether to base their decision about the intensity of their corrective actions on the system state solely considering the current level of the stock, or by *projecting the stock levels including future incoming quantities*. Thus, a manager that fully considers the status of the supply line is less likely to overreact to discrepancies to the target objective. Consider for example a productive system facing a constant demand of 20 pcs/day where the manager's duty is to keep inventory levels always above 100 pcs. Suppliers require instead 5 days to fulfil orders. Imagine 120 pcs are kept in inventory at the beginning. During the first day the manager sees her stock lowering to 100, hence it issues a replenishment order of 120 pcs, covering today's consumption that led to the deviation from the target (e.g 20 pcs) and the 5-days coverage required to fulfil her expectations about customer orders during replenishment lead time (e.g. 20 pcs/day * 5 days = 100 pcs). If the manager keeps discarding the status of the supply line to its stock, the next day it will be pushed even harder by seeing the stock lowering to 60 pcs and issuing a replenishment order of 140 pcs. The suppliers receive the new order and schedules it so as to be delivered in 5 days. If this process continues, at time 5, the stock scratching at 20 pcs gets finally replenished by the initial order of 120 pcs, jumping to 140 pcs and relieving the manager pressure. Unfortunately, on the next day, also the order of 140 issued on day 2 arrives, letting inventory spike to 270 pcs. At the end of this cycle the manager sees its stock skyrocketing well above her targeted amounts, inducing excess accumulations, and it could be avoided by considering the current material in transit. This behaviour is extensively described by Sterman in its famous *Beer Simulation Game* and clearly shows an example of *agents bounded rationality* in action.

Finally, the above formulation utilises the well-known *anchoring and adjustment theory* introduced in Sterman about *agents' beliefs creation* starting from known reference points. In this formulation, the *anchors* of the decision is the *Desidered Replenishment Production* which is then adjusted to match the Desidered Production Rate with the desired target levels of WIP inventory.

Desired Replenishment Production. The desidered replenishment volume to keep the Finished Goods Inventory aligned with targeted levels, without considering the current status of the supply line.

```
Context = Endogenous          Type = Auxiliary Variable          UOM
= units/day

Desired Replenishment Production =
  INTEGER
   (
     Expected Customer Orders + FG inventory adjustments,
   )
```

In the above formulation, the *anchor* of the decision are the *Expected Customer Orders* which are then adjusted to match the Desidered Replenishment Rate with the desired target levels of the Finished Goods Inventory.

Expected Customer Orders. Being defined by variables pertaining to the Demand Forecasting Module, its formu is detailed in Par. 5.3.1.4.

WIP. Accumulation of production orders released in previous timestamps of the simulation that are currently flowing along the line. It groups all intermediate production stages in the BOM. It represents the supply line to the Finished Goods Inventory stock.

```
Context = Endogenous                Type = Stock                     UOM
= units

WIP  =  INTEGRAL(Daily  Production  starts  -  Throughput,  WIP,  Desired
WIP)
```

The initial condition set to be equal to *Desidered WIP* is mandatory to ensure the *suboptimal initial equilibrium state of the stock*.

Desidered WIP. The desired level of the Finished Goods Inventory supply line so as to yield the desired replenishment volumes required during a full manufacturing cycle. The fuzzy MAX function is used to ensure non-negativity of a stock quantity representing material objects.

```
Context = Endogenous          Type = Auxiliary Variable          UOM
= units

Desired  WIP  =  MAX(Desirable  Replenishment  Production*Decoupled  Lead
Time, 0)
```

WIP adjustments. The response of the managers to deviation of WIP from targeted WIP, considering the reaction time required to collect data about the stock levels and take action.

```
Context = Endogenous ;        Type = Auxiliary ;UOM = units/day ;
```

```
WIP adjustments = (Desired WIP-WIP)/WIP adjustment time
```

The above formulation assumes a linear adjustments logic applied by the system manager, as done in Sterman.

WIP adjustment time. Manager reaction time required to detect shifts in WIP levels and take corrective actions.

```
Context = Exogenous     ;                 Type = Constant ;       UOM
= days ;
```

Finished Good Inventory. The accumulation of all available finished goods ready for shipment. It represents the state variable of a real warehouse of finished products set at the end of each production line. It represents one of the most important variables of the model.

```
Context = Endogenous ;              Type = Stocks      ;
      UOM = units ;

Finished Good Inventory =
    INTEGRAL(Throughput-Shipments,  Finished  Good  Inventory,  Target
Stock)
```

Target Stock. The desired level of the Finished Goods Inventory required to guarantee stock-out protection considered the actual manager expectations of customer orders.

```
Context = Endogenous ;        Type = Auxiliary Variable     ;     UOM
= units ;

Target   Stock   =   Expected   Customer   Orders*(Customer   Tolerance
Time+Finished Good Safety Stock Coverage)
```

The above formulation assumes the *Customer Tolerance Time* being the Sterman equivalent to the Minimum Order Processing Time.

FG adjustments. The response of the managers to deviation of Finished Goods Inventory from *Target Stock*, considering the reaction time to detect changes to the stock.

```
Context = Endogenous ;        Type = Auxiliary       UOM = units/day
;

FG adjustments = (Target Stock-Finished goods inventory)/FG Inventory
Adjustment Time
```

FG Inventory adjustment Time. Manager reaction time required to detect shifts in Finished Goods Inventory levels and take corrective actions.

```
Context = Exogenous     ;            Type = Constants;              UOM
= days ;
```

Customer Tolerance Time. The minimum time the customer is willing to wait upon order release before seeking for alternative procurement.

```
Context = Exogenous ;         Type = Constants ;             UOM      =
days ;
```

Finished Good Safety Stock Coverage. The desired minimum Finished Goods inventory days of coverage with respect to the expected customer demand. It is the result of the common company practice of setting a determined Service Level for different SKUs.

```
Context = Exogenous     ;            Type = Constants ;             UOM
= days ;
```

Throughput. Daily effective replenishment output of the productive system. It represents the net quantity pushed upstream by a production order released during the previous manufacturing cycle.

```
Context = Endogenous            Type = Flow
      UOM = units/day

Throughput = Potential Throughput
```

This quantity might be affected by losses due to scrapped materials generated by overloading conditions of the production line. The *WIP scrapping rate* is an addition of the proposed model to the Sterman base case and it is discussed in Par. 5.3.3.1.3.

Potential Throughput. The theoretical output if no losses occurred during the manufacturing stage.

```
Context = Endogenous          Type = Auxiliary             UOM      =
units/day

Potential Throughput =
DELAY    MATERIAL(Daily    Production    starts,    Decoupled    Lead
Time,Shipments, 0)
```

Decoupled Lead Time. The manufacturing lead time (MLT).

```
Context = Exogenous                        Type = Constant  UOM      =
units/day

Decoupled Lead Time = 56 days      (default)
```

As seen in Chap. 2, the concept of Decoupled Lead Time (DLT) is a novelty introduced by DDMRP that differs from the conventional concept of MTL. However, by assuming in the proposed model that only 2 buffers are placed in the BOM, namely on Raw Materials and Finished Goods, the DLT can be mapped into the traditional MLT given that if only 2 buffers are considered then the time to move materials between them, namely the DLT, equals to the MLT. This assumes the downstream buffer is not stocked-out, as in the original DDMRP definition of DLT.

Shipments. The daily actual shipped goods by the system.

```
Context = Endogenous                Type = Flow              UOM      =
units/day

Shipments = MIN(Max shipment rate, MAX(Desidered Shipment Rate, 0)) ;
```

Being the Desidered Shipment Rate included in the formulation, it represents the connection point between the Finished Goods Inventory Module and the Order Fulfilment module. It is worth noticing that in the current formulation shipments and customer orders are numerically equivalent but they refer to different flows, respectively materials flows as opposed to information flows.

Desidered Shipment Rate. Being defined by variables pertaining to the Order Fulfilment Module, its formulation and description it is detailed in in Par. 5,3.1.5.

Max Shipment Rate. The actual sustainable shipment rate provided by the current inventory on-hand and daily throughput.

```
Context = Endogenous          Type = Auxiliary        UOM = units/day

Max Shipment Rate = MAX(Finished goods inventory,0) + Throughput
```

The above formulation entails a slight change with Sterman, given that in Sterman the Max Shipment Rate is limited by the exogenous factor of Minimum Order Processing Time. In the proposed model it is assumed that the manager is willing to fulfil all orders she can in a day.

Actual Inventory Coverage. The current days of coverage equivalent of the Finished Goods Inventory if Shipments stay fixed at current levels.

```
Context = Endogenous          Type = Auxiliary        UOM = units/day

Actual Inventory Coverage = XIDZ(Finished goods inventory, Shipments,
0) ;
```

Actual Inventory Coverage. The current days of coverage equivalent of the Finished Goods Inventory if Shipments stay fixed at current levels.

```
Context = Endogenous          Type = Auxiliary        UOM = units/day

Actual Inventory Coverage = XIDZ(Finished goods inventory, Shipments,
0) ;
```

5.3.1.2. Raw Materials Inventory module

Fig. 5.4 introduces the base Stock and Flow diagram describing the Raw Materials inventory dynamics, replicating most of what was done in Sterman with some slight changes happening mostly on the Suppliers side (see Par. 5.3.1.3). Slightly different Table functions are used to model *Planners Expectations about Suppliers Lead Time*s and for *Components availability*. The Raw Materials Inventory module applies the same concepts of the stock management problem seen for the Finished Goods Inventory Module but, in this case, *the stock of raw materials aggregates all the different inputs used to manufacture one functioning unit of the finished product*. Hence, such formulation of raw materials cannot represent typical multi-echelon product BOMs. To cope with the limitation, the module reduces all components to one distinct instance called "*raw materials*" and uses auxiliaries and tables functions so as to simulate an average reasonable availability behaviour of such an aggregated component. On the other hand, as observed in Sterman, building a model that reproduces BOMs with extreme fidelity guarantees an extreme overcomplication of the model (even from a time-complexity side) and rarefaction of the analysis focus, which in turn probably results in marginal accuracy gains.

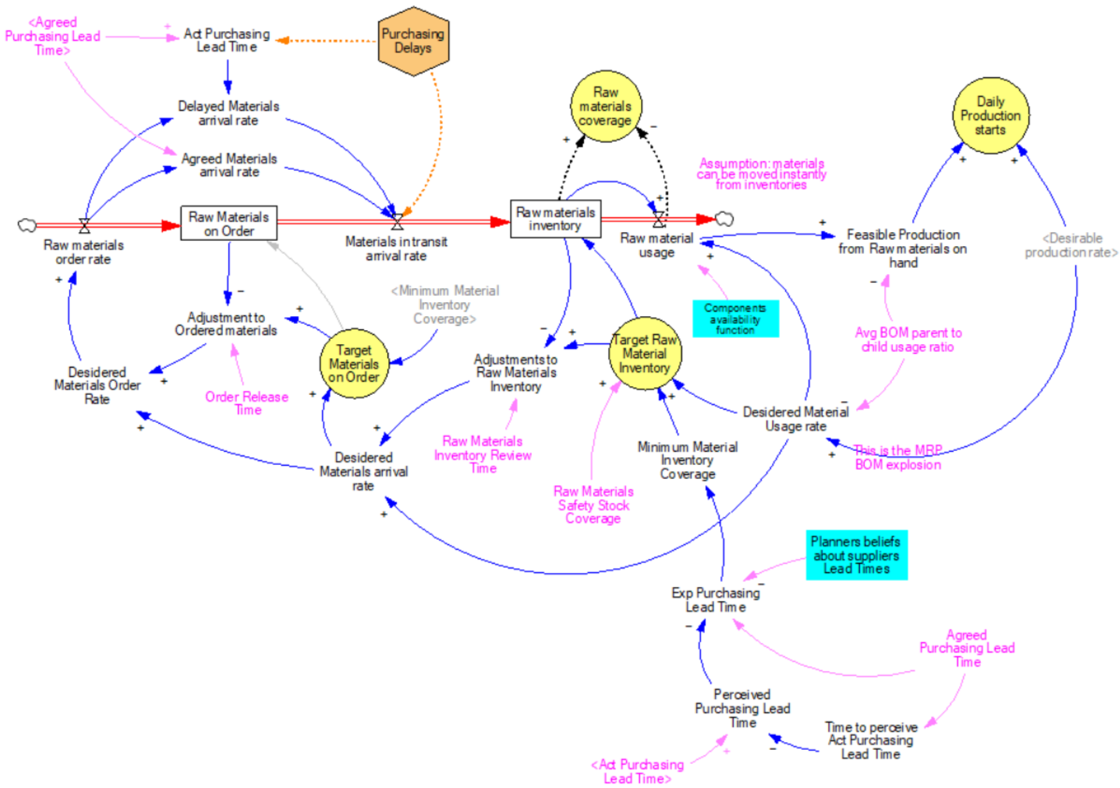


Fig. 5.4. *Stock and Flow diagram of the Raw Materials Inventory Module*

Feasible Production from Raw materials on hand. The equivalent volumes of finished goods producible with the total raw materials inventory on hand. It represents the connection point between the Finished Goods Inventory Module and the Raw Materials Inventory one, being included in the *Daily Production Starts* formulation.

```
Context = Endogenous          Type = Auxiliary          UOM     =
units/day

Feasible Production from Raw materials on hand =
Raw material usage/Avg BOM parent to child usage ratio
```

Avg BOM parent to child usage ratio. It represents the first artifice induced by the Raw Materials Inventory module assumptions: being a typical product BOM made of multiple components required in different quantities on a functioning unit, this variable defines the average of such requirements. If all components are used in the same quantities, this variable represents the exact parent-to-child BOM ratio.

```
Context = Exogenous           Type = Auxiliary          UOM     =
dimensionless
```

In the proposed model such parameter is set to 1 by default, representing a product BOM where all components are used only once to make a functional unit, but it can be varied during the simulation.

Raw material usage. Represents the *quantity of the aggregate component raw material* withdrawn from the raw material reserves. Being the finished goods production a "components aggregating" function, this quantity is always bigger than or equal to the *Feasible Production from Raw materials on hand*.

```
Context = Endogenous            Type = Flow                 UOM     =
units/day

Raw material usage=
MAX(
 0,
INTEGER(
 Desidered Material Usage rate*
 Components availability
(
   XIDZ
    (
      Raw materials inventory,
            MAX(Desidered Material Usage rate, 0),
      1
   )
)
 )
)
```

Desired Material Usage Rate. It represents the desired amount the manager of the system would like to withdraw from Raw Materials Inventory so as to *execute the production plan without delays*.

```
Context = Endogenous            Type = Auxiliary            UOM     =
units/day

Desired Materials Usage Rate = INTEGER(Desirable production rate*Avg
BOM parent to child usage ratio)
```

Being the *Desirable Production Rate* included in the formulation, the *Desired Materials Usage Rate* represents an information bridge between the state of the Finished Goods Inventory Module and the Raw Materials Inventory one. Such bridging represents the *dependent demand requested to the downstream echelon* from the upstream one, thus it is the SD representation of the MRP explosion and DDMRP decoupled explosion.

Components availability. It represents the second artifice induced by the Raw Materials Inventory module assumptions: being the Raw Materials Inventory stock representing also the total inventory of raw materials on-hand and, the lower this value it gets, the higher the probability of some individual components to be stocked-out. Thus, a table function relates such probability with the status of the Raw Materials Inventory stock normalised by the Desired Raw Materials Usage Rate.

```
Context = Endogenous          Type = Look-up          UOM = dimensionless
```

Input	Output
0	0
0.2	0.04
0.4	0.25
0.5	0.4
0.6	0.55
0.8	0.75
1	1

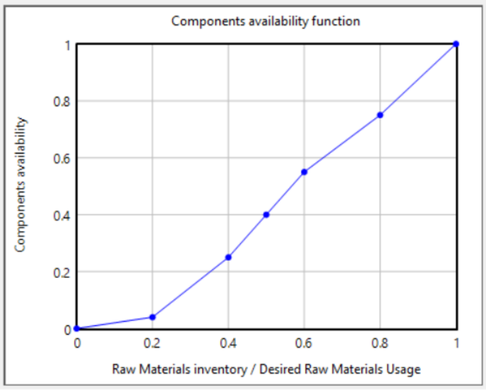


Fig. 5.5. *Table function definition of the Components Availability*

Raw Materials Inventory. The accumulation of all purchased raw materials ready to feed production lines. It represents the state variable of a real warehouse of raw materials set at the beginning of each production line.

```
Context = Endogenous          Type = Stock          UOM = units

Raw Materials Inventory = INTEGRAL(Raw Materials arrival rate-Raw material usage-Raw materials obsolescence rate, Target Raw Material Inventory)
```

Target Raw Materials Inventory. The desired level of the Raw Materials Inventory so as to always guarantee enough raw materials to never constrain upstream production plan requirements thus protecting Raw Materials from stock-outs during a full replenishment cycle.

```
Context = Endogenous          Type = Auxiliary          UOM = units

Target Raw Materials Inventory =
MAX(Desidered Material Usage rate*(Raw Materials Safety Stock Coverage+Material Replenishment Inventory Coverage), 0)
```

Raw Materials Inventory Safety Stocks Coverage. The desired minimum Raw Materials Inventory days of coverage with respect to the current production plan upstream requirements.

```
Context = Exogenous              Type = Auxiliary            UOM      =
days
```

Material Replenishment Inventory Coverage. The desired minimum Raw Materials Inventory days of coverage with respect to the expected delivery lead times from suppliers. Planners are assumed to always try to build a raw materials inventory coverage 1-day greater than their expectation about suppliers' replenishment delay.

```
Context = Exogenous              Type = Auxiliary            UOM      =
days

Material  Replenishment  Inventory  Coverage  =  Exp  Purchasing  Lead
Time+1
```

Expected Purchasing Lead Time. The current planners expected delivery dates with respect to what suppliers claim.

```
Context = Endogenous             Type = Auxiliary            UOM      =
days

Expected Purchasing Lead Time =
Agreed  Purchasing  Lead  Time*Planners  beliefs  about  suppliers  Lead
Times(XIDZ(Perceived  Purchasing  Lead  Time,  Agreed  Purchasing  Lead
Time, 1))
```

Agreed Purchasing Lead Time. The delivery promised delay contracted with suppliers by Schedule Agreements (see Chap. 3).

```
Context = Exogenous              Type = Auxiliary            UOM      =
days
```

Perceived Purchasing Lead Time. The observed suppliers delivery delay. Being the suppliers lead time reviewing process entailing different kind of delays (e.g. reporting to procurement, waiting real due dates, ..) such expectation adjustment process is described by the SMOOTH function.

```
Context = Endogenous             Type = Auxiliary            UOM      =
days

Perceived Purchasing Lead Time =
SMOOTH(Act Purchasing Lead Time, Time to perceive Act Purchasing Lead
Time)
```

The SMOOTH function applies *first-order smoothing* to the Actual Purchasing Lead Time signal, thus creating a cascaded information delay. The result of this process can be seen in

Fig. 5.6 and it is conventionally used to model situations where the decision maker tries to filter out high frequency oscillations in the signal to prefer average trends.

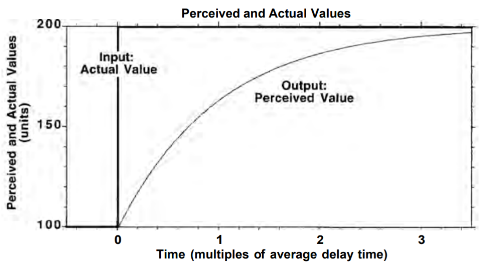


Fig. 5.6. *The effect of the SMOOTH function applied on a step input signal increase*

Actual Purchasing Lead Time. Being defined by variables pertaining to the Suppliers Module, its formulation is detailed in Par. 5.3.1.3.

Time to Perceive Actual Purchasing Lead Time. The time required to planners so as to detect changes in the supplier's delivery delays.

```
Context = Endogenous             Type = Auxiliary             UOM     =
days

Time to Perceive Actual Purchasing Lead Time = MIN(Agreed Purchasing
Lead Time, Actual Purchasing Lead Time) + 5
```

Thus, planners become aware of a shift in the delivery lead time as soon as either the order gets delivered beforehand or promised dates get infringed. However, the reviewing processes of such a condition requires a full 5-days working week to take place to successfully engage procurement too.

Planners Beliefs about Suppliers Lead Times. It represents the planner's distrust in their suppliers' claims about Agreed Purchasing Lead Times. Such a relationship is depicted by a table function relating the Perceived Purchasing Lead Times with what planners really think the supplier Actual Delivery Lead Time is.

```
Context = Exogenous              Type = Lookup                UOM     =
days
```

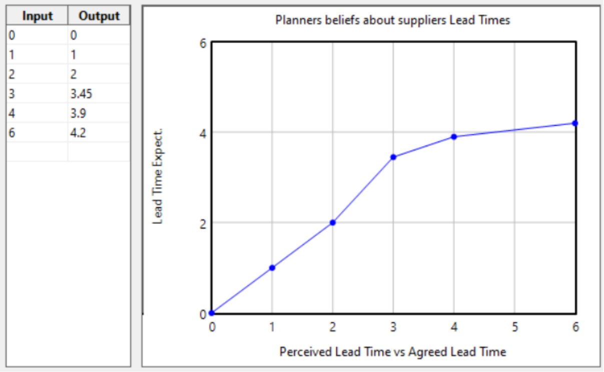


Fig. 5.7. *Lookup of the Planner beliefs about suppliers Lead times*

It is worth noticing that the 45° line represents all those cases where planners believe in their suppliers claims, whereas all points lying above the bisector line represents all those cases where planners believe suppliers claims are just wishful underestimates. Finally, when perceived suppliers delivery lead times overshoot substantially Agreed Purchasing Lead Times, planners corrective action of suppliers lead times reaches a plateau and stops increasing.

Adjustments to Raw Materials Inventory. The response of the managers to deviation of Raw Materials Inventory from *Target Raw Materials Inventory*, considering the reaction time needed to detect changes to the stock.

```
Context = Endogenous            Type = Auxiliary            UOM     =
units/day

Adjustments to Raw Materials Inventory =
(Target Raw Material Inventory-Raw materials inventory)/Raw Materials
Inventory Review Period
```

Raw Materials Inventory Review Period. The time required for planners to review the status of all Raw Materials on Hand by using the SAP software manual trasfactions.

```
Context = Exogenous             Type = Auxiliary            UOM = day
```

From what is seen in Chap. 2, introducing the *Industrial Inventory DP* to the daily working routines of material planners it is equivalent to saying that the value of the Raw Materials Inventory Review Period lowers dramatically.

Raw Materials Coverage. The current days of coverage equivalent of the Raw Materials Inventory if customer orders stay at current levels.

```
Context = Endogenous            Type = Auxiliary            UOM     =
units/day

Raw Materials Coverage = XIDZ(Raw materials inventory, Raw material
usage, 0)
```

Desired Materials Order Rate. The desired size of the purchasing order to issue so as to maintain the materials replenishment cycle in equilibrium.

```
Context = Endogenous            Type = Auxiliary            UOM     =
units/day

Desired Materials Order Rate = INTEGER(Desidered Materials arrival
rate+Adjustment to Ordered materials)
```

Desired Material Arrival Rate. The desired rate of materials deliveries from suppliers so as to maintain the targeted Raw Materials Inventory coverage while satisfying the production plans requirements too.

```
Context = Endogenous            Type = Auxiliary            UOM     =
units/day

Desired Material Arrival Rate = INTEGER(Desidered Material Usage
rate+Adjustments to Raw Materials Inventory)
```

Raw Materials On-Order. The desired level of the Raw Materials Inventory so as to always guarantee enough raw material to never constrain upstream production plan requirements.

```
Context = Endogenous            Type =Stock                 UOM     =
units

Raw Materials On-Order = INTEGRAL(Raw materials order rate-Raw
Materials arrival rate, Target Materials On-Order)
```

Target Materials On-Order. The desired level of the Raw Materials Inventory supply line so as to yield the desired replenishment volumes on proper dates and close the material replenishment cycle.

```
Context = Endogenous            Type = Auxiliary            UOM     =
units

Target Materials On-Order = Material Replenishment Inventory
Coverage*Desidered Materials arrival rate
```

Adjustment to Ordered Materials. The response of the managers to deviation of Materials On-Order stock from the Target Materials On-Order, considering the reaction time to detect changes to the stock.

```
Context = Endogenous           Type = Auxiliary          UOM     =
units/day

Adjustment  to  Ordered  Materials  =  (Target  Materials  on  Order-Raw
Materials on Order)/Order Release Time
```

Order Release Time. The time required to materials planners to review all Open Schedule Lines, fill the required documents and officially release to the suppliers online portal a replenishment purchase order.

```
Context = Exogenous            Type = Auxiliary          UOM = day
```

Raw Materials Order Rate. The actual size of the released order to suppliers.

```
Context = Endogenous           Type = Flow               UOM     =
units/day

Raw Materials Order Rate = MAX(0, Desidered Materials Order Rate)
```

Raw Materials Arrival Rate. Being defined by variables pertaining to the Suppliers Module, its formulation is detailed in Par. 5.3.1.3.

5.3.1.3. "Suppliers" Module

Fig. 5.8 introduces the "Suppliers" Module embedded as a *tail* to the Raw Materials Inventory Module. Differently from Sterman, the proposed model is not duplicated so as to create another instance of a company in the supply-chain representing a supplier. Rather, suppliers are seen as almost perfect entities that upon receipt of a schedule line they release material after a certain Lead Time. This approach was mandatory for the reasoning in Paragraph 5.##. However, a basic logic is deployed so as to recreate the common scenario of delivering delays from suppliers, by applying a random pink noise generator to the Agreed Purchasing Lead Time used to set the material release delay. Due to its simplicity, the Suppliers Module is directly embedded in the Raw Materials Inventory Model.

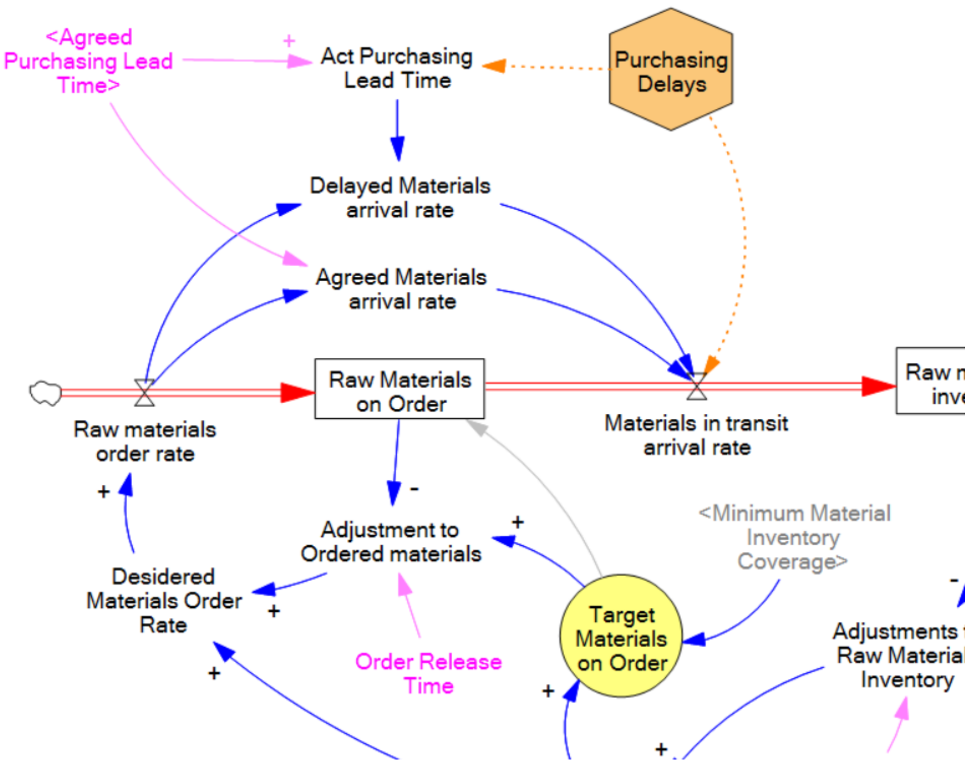


Fig. 5.8. *Implementation of Suppliers in the proposed model*

Raw Materials Order Rate. Being defined by variables pertaining to the Suppliers Module, its formulation is detailed in Par. 5.3.1.2.

Raw Materials Arrival Rate. The daily actual purchased material arrivals at the plant. Its value depends on whether suppliers are considered efficiently responding to orders or impacting the replenishment plan by arbitrary delays.

```
Context = Endogenous          Type = Flow          UOM     =
units/day

Raw Materials Arrival Rate =
INTEGER(IF THEN ELSE(Purchasing Delays=0, Agreed Materials arrival
rate, Delayed Materials arrival rate))
```

Agreed Materials Arrival Rate. The Raw Materials arrival rate when raw materials replenishment is executed by suppliers as planned by the Purchasing Agreement.

```
Context = Exogenous           Type = Auxiliary     UOM     =
days

Agreed Materials Arrival Rate = DELAY MATERIAL(Raw materials order
rate, Agreed Purchasing Lead Time, Desired Raw Materials Order Rate,
0)
```

The use of DELAY MATERIAL entails a slight difference with what is done in Sterman, where materials resupplies from suppliers are modelled by means of a first-order delay. The initial delay condition is set so as to match the initial Desired Raw Materials Order Rate.

Purchasing Delays. A boolean value allowing to activate the *Purchasing Delays Scenario*. When TRUE, the actual supplier's response to commanded Raw Materials Orders do not always match with the replenishment plan.

```
Context = Endogenous            Type = Scenario            UOM     =
dimensionless
```

Actual Purchasing Lead Time. The actual suppliers' response to commanded Raw Materials orders when the *Purchasing Delays* scenario is turned on. The deviation from agreed conditions is modelled by means of a random pink noise generator fed with the Agreed Purchasing Lead Time as noise average value, and a standard deviation uniformly distributed between 1 and 10 days. The degree of autocorrelation between noise values is set to a 5-days full working week.

```
Context = Endogenous            Type =Auxiliary            UOM     =
days

Actual  Purchasing  Lead  Time  =  IF  THEN  ELSE(Purchasing  Delays=1,
MAX(Agreed Purchasing Lead Time, RANDOM PINK NOISE(Agreed Purchasing
Lead  Time,  RANDOM  UNIFORM(1,  10,  0),  5,  Agreed  Purchasing  Lead
Time)), Agreed Purchasing Lead Time)
```

Delayed Materials Arrival Rate. The Raw Materials arrival rate when raw materials replenishment is not executed by suppliers as planned by the Purchasing Agreement.

```
Context = Endogenous            Type = Auxiliary            UOM     =
units/day

Delayed Materials Arrival Rate = DELAY MATERIAL(Raw materials order
rate, Act Purchasing Lead Time, 0, 0)
```

5.3.1.4. Demand Forecasting module

Fig. 5.9 introduces the base Demand Forecasting module, an exact replica (at this development stage) of what was done in Sterman apart from the additional feature of being able to select different demand scenarios to launch the model against. This will be essential to perform a rapid comparative analysis when data of multiple datasets will be investigated. Finally, to simulate more realistic demand trends, it is possible to let the average demand signal pass through a "noise gate" defined by a random pink noise generator (Fig. 5.10). This can be turned on and off depending on the scope of the analysis. Finally, the process of exponential smoothing of the final demand signal is applied as introduced in Sterman.

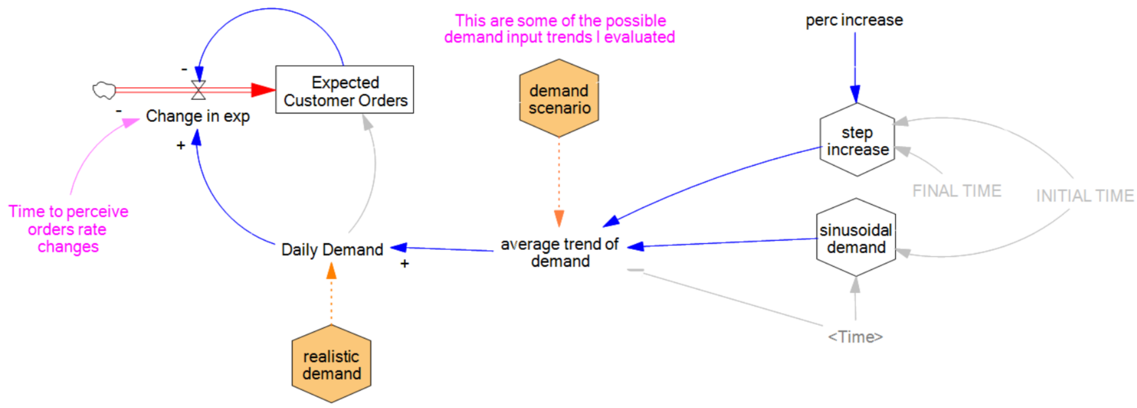


Fig.5.9. *Stock and Flow Diagram of the base Demand Forecasting Module*

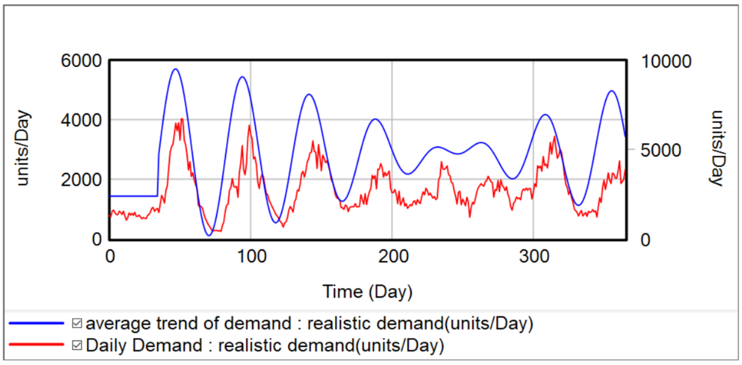


Fig.5.10. *Simulation of a realistic demand trend from an average trend*

Average Trend of Demand. The average trend of demand followed by the Daily Demand. This value is selected by means of the *Demand Scenario*

```
Context = Endogenous          Type = Auxiliary          UOM    =
units/day
```

Demand Scenario. It allows to run the model under different Average Trend of Demand inputs. In the final version of the proposed model 5 demand scenarios are available.

```
Context = Endogenous          Type = Scenario           UOM    =
dimensionless

IF    demand scenario=0 THEN  Constant Demand = 10000/7
IF    demand scenario=1 THEN  Step Increase
IF    demand scenario=2 THEN  Sinusoidal Demand
IF    demand scenario=4 THEN  Whirlpool inventory dataset  (see Chap.
6)
```

```
IF    demand scenario=4 THEN  DDI simulation dataset      (see  Par.
5.3.6)
```

Realistic Demand. It allows to alter the Average Trend of Demand so as to generate a more realistic demand trend derived from the average one. When the *Realistic Demand scenario* is set to FALSE, the average trend of demand equals the Daily Demand.

```
Context = Endogenous            Type = Scenario            UOM     =
dimensionless
```

Daily Demand. The actual daily amount of goods requested by the market to the company. If the *Realistic Demand scenario* is set to TRUE the incoming Average Trend of Demand signal is passed as the average value of a random pink noise generator so as to generate a 5-days autocorrelated signal with a coefficient of variation (CoV) equal to 0.2.

```
Context = Endogenous            Type = Auxiliary           UOM     =
units/day

Daily Demand =INTEGER( IF THEN ELSE(realistic demand=1,  MAX(RANDOM
PINK NOISE(average trend of demand,0.2*average trend of demand, 5,
0), 0), average trend of demand))
```

Step Increase. A selectable average demand trend presenting a sudden fixed % Increase of its base value set equal to 1428 units /day.

```
Context = Exogenous             Type = Auxiliary           UOM     =
dimensionless

Step   Increase   =   (10000/7)*(PULSE(0,FINAL   TIME+1)+(PULSE(FINAL
TIME/12,FINAL TIME)*(perc increase)))
```

% Increase. The percentual amount of the demand step increase.

```
Context = Exogenous             Type = Auxiliary           UOM     =
dimensionless
```

Sinusoidal Demand. A selectable average demand trend described by a sinusoidal function. It is useful to simulate demand trend affected seasonality and it provides a highly dynamic input to test the model against.

```
Context = Exogenous             Type = Auxiliary           UOM     =
units/day
```

Sinusoidal Demand =

$$\frac{10000}{7} * (PULSE(0,\ 35) + ((2 + sin(\frac{Time-35}{2000*240}) + sin(\frac{35*(Time-35)}{240})) * PULSE(35,\ FINAL\ TIME)$$

Expected Customer Orders. The first-order smoothed manager expectations of future customer orders.

```
Context = Endogenous            Type = Stock                UOM     =
units

Expected Customer Orders = INTEGRAL(Change in exp, Daily Demand) ;
```

It is worth noticing that the stock and flow representation of this variable is the same implemented by a SMOOTH function.

Change in Expectations. The forecasting error affecting manager's beliefs about future customer orders with respect to actual daily demand, considering the time required to execute countermeasures.

```
Context = Endogenous            Type = Auxiliary            UOM     =
units/day

Change in Expectations = (Daily Demand-Expected Customer Orders)/Time
to perceive orders rate changes
```

Time to Perceive Orders rate changes. The manager's reactiveness in accepting a shift from its beliefs about customer orders.

```
Context = Endogenous            Type = Auxiliary            UOM     =
days
```

5.3.1.5. Order Fulfilment module

Fig. 5.11 introduces the base Order Fulfilment Module, a replica of what was done in Sterman but considering a slightly different formulation for the *Desired Shipment Rate.* Indeed, in the proposed model the Desired Shipment Rate is the one needed by the system to meet all "open demand", thus all backorders and daily demand, whereas in Sterman only backorders are considered. Indeed, in Sterman new orders are purposely fractionally fulfilled at each iteration so as to maintain a certain *Target Delivery Delay*. This delay represents in Sterman the "*targeted time elapsed between order receipt and shipment*", namely the agreed purchasing lead time, and it is used to determine the

Desired Shipment Rate (Sterman) = Backlog/Target Delivery Delay

This value is recognized by Sterman as the "*shipment rate that would allow the company to fulfil **new** orders within its targeted delivery delay*". Thus, if the Actual Fulfilment Rate always equals the Desired Shipment Rate then all orders will be met within the Targeted

Delivery Delay. On the other hand, in Sterman there is no penalization for delayed orders, thus orders get accumulated indefinitely as backorders waiting to be fulfilled at potentially any speed the system is capable of maintaining. When the backorder increases, then the desired speed of fulfilment increases as well, but if the backorder stock keeps increasing for an extended period of time, the urgency of fulfilling backorders should increase more on the already "old" orders than the new one. In the Sterman formulation the order fulfilment speed increases linearly with the increase in the backorder stock but does not take into account that in the stock "orders of different ages" gets accumulated. Older orders should be fulfilled faster than the new incoming backorders to prevent them from being cancelled.

A possible approach to tackle the issue could try to evaluate the average age of the backorders and use that to determine the actual speed of fulfilment. Unfortunately, no simple approach was found to achieve this given that each order "decay alone" thus an ageing chain of length equal to the customer tolerance time would be needed to model such a concept. Of course, this representation would be extremely static and specific for a single CTT value. Thus the selected approach the company undergoes to fulfil backorders is a "As Soon as Possible" one. This is equivalent of saying that in the proposed model the Targeted Delivery Delay is always set equal to same day delivery, thus

Target Delivery Delay (proposed model) = 1 ;

Desired Shipment Rate (Sterman) = Incoming Orders + Orders on Allocation ;

Putting this on another perspective, a company that wants to meet specific Purchasing Lead Times is limited by its capability of satisfying orders within that target. To do so, it can either exploit quantities already available, labelling them as sold and planning their delivery on the order due date, or it must ramp up production so as to obtain the missing units within the due order date. The above reasoning is pursued in the proposed model formulation. Finally, the Daily Service Level is evaluated.

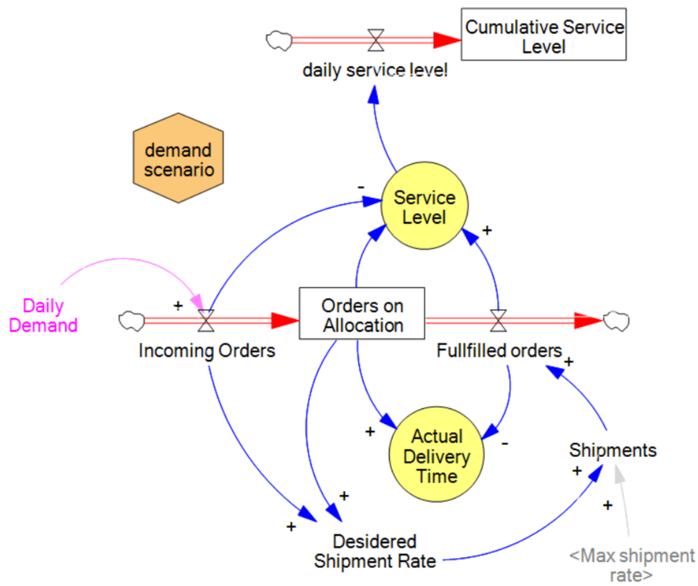


Fig.5.11. *Stock and Flow diagram of the base Order Fulfilment Module*

Desidered Shipment Rate. The shipment rate the manager would like to meet in order to always hit 100% fill rates and service levels. It represents the connection point between the Finished Goods Module and the Order Fulfilment Module.

```
Context = Endogenous          Type = Auxiliary          UOM     =
days

Desired Shipment Rate = Orders on Allocation+Incoming Orders
```

Orders On-Allocation. The accumulation of all daily unfulfilled orders waiting to be fulfilled based on FIFO ASAP logic.

```
Context = Endogenous          Type = Stock              UOM     =
orders

Orders On-Allocation = INTEGRAL(Incoming Orders - Fulfilled orders,
0)
```

Incoming Orders. The daily ordered amounts requested to the company.

```
Context = Endogenous          Type =Flow           UOM          =
orders/day

Incoming Orders = Daily Demand
```

Fulfilled Orders. The portion of daily qualified orders that the system is able to satisfy. As was said in Par. 5.3.1.1, in the current formulation shipments "nullify" pending orders, letting Fulfilled Orders and Shipments numerically equivalent, but they refer to different flows.

```
Context = Endogenous          Type = Flow               UOM     =
orders/day

Fulfilled Orders = Shipments
```

Daily Demand. Being defined by variables pertaining to the Demand Forecasting Module, its formulation is detailed in Par. 5.3.1.4.

```
Context = Exogenous           Type = Auxiliary          UOM     =
orders/day
```

Shipments. Being defined by variables pertaining to the Demand Forecasting Module, its formulation is detailed in Par. 5.3.1.1.

Actual Delivery Time. The actual time required by the system to deliver the accumulated backorders.

```
Context = Endogenous            Type = Flow                 UOM     =
orders/day

Actual Delivery Time = INTEGER(XIDZ(Orders on Allocation, Fulfilled
orders), 1))
```

Service Level. The ratio between the daily satisfied demand and the total daily qualified
Orders.

```
Context = Endogenous            Type =Auxiliary       UOM           =
dimensionless

Service Level = XIDZ(Fulfilled orders, Incoming Orders+Orders on
Allocation, 1)
```

Cumulative Service Level. The cumulative sum of all the obtained values of the service level.

```
Context = Endogenous            Type = Stock                UOM     =
dimensionless

Cumulative Service Level = INTEGRAL(Service Level, 0)
```

While this metric has a poor real sense, it is exploited so as to summarise the overall system performance after a full simulation. Thus, by comparing the cumulative service level it is possible to have a first-order idea about which inventory policy generated the highest performance. In other words, if at any simulation timestamp a policy yields higher service levels than another, it is reasonable to say that such policy outweighs the latter one.

5.3.2. Wave I validation : Model response to a step increase in customer orders

5.3.2.1. Testing conditions

As anticipated in Par. 5.3, Validating W-I meant *having a model which reproduced the same trends obtained in Sterman, Chapt. 18* when a **sudden 20% step-increase stimulus** from the initial equilibrium condition set by the daily customer order curve was applied, as shown by Fig. 5.12. The list of all parameters settings to run the validation phase is given in Tab. 5.1. All exogenous variables and company parameters (e.g. Stock adjustment times, Supplier Lead Times, Material Usage Ratio, Manufacturing Lead Times, ...) have been set to match with what reported in Sterman. Being the Sterman model based on weekly time buckets, the reported value in Tab. 5. are reconducted on a daily basis, being the proposed model instead based on daily time buckets.

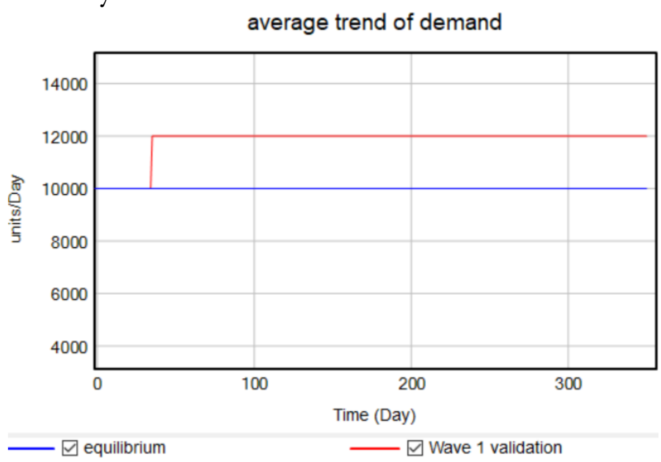


Fig.5.12. *Step perturbation from equilibrium for Customer Orders used to validate W-I*

Finished Good Inventory parameter	**Validation WI**	**Raw Materials Inventory parameter**	**Validation WI**	**Demand Forecasting Module parameter**	**Validation WI**
Decoupled Lead Time	56 days	Avg BOM parent to child usage ratio	1 pcs/pcs	*Customer Orders*	See Fig. 5.12
FG Inventory adjustment time	56 days	Raw Materials Safety Stock Coverage	6 days	*Time to perceive orders rate changes*	56 days
WIP adjustment time	14 days	Raw Materials Inventory Review Period	14 days	**Order Fulfilment Module parameter**	**Validation WI**
Finished Goods Safety Stock Coverage	14 days	Order Release Time	14 days	*Customer Tolerance Time*	14 days
		Agreed Purchasing Lead Time	7 days		

Tab. 5.1. *Parameters setting for W-I validation*

5.3.2.2. Discussion of the model response

As it can be seen by Fig.5.13 and 5.14, **all model profiles match exactly apart for the Desidered Shipment Rate and the Actual Delivery Time** : in the proposed model both metrics stay always equal or lower than what reported in Sterman. This is due to the different approach taken by the modeller regarding the orders fulfilment behaviour.

As detailed in Par. 5.3.1.5, in the proposed model the Order Fulfilment Module always tries to release all the backorders and the incoming ones, thus applying a FIFO logic and assigning no order priority. In other words, in the proposed model the Desidered

Shipment Rate is the shipment rate that would be needed to always achieve a unitary Service Level. This condition pushes the company to “operate full throttle”, targeting in the best-case daily fulfilment of all orders, thus an Actual Delivery Time equal to 0. *Counter-intuitively*, while the previous is true, thus one might expect higher desidered shipment rates, the Desidered Shipment Rate stays lower than what is done in Sterman because orders tend to accumulate less as backorders. Indeed, a company that always tries to empty the order on-allocation stock is targeting a minimization of future efforts, thus lowering future desidered shipment rates. Moreover, companies that act in this way put customer satisfaction ahead of everything else. Orders get cancelled if they cannot be fulfilled within promised delivery dates, the customer tolerance time. On the other hand, this approach can be heavily questioned claiming that in this way there is no order prioritisation, a rather common practice in many companies. Moreover, it is not said that all clients appreciate earlier-than-scheduled deliveries. Indeed, if the final client is not the final user of the finished product (e.g. another manufacturer) then it is likely that the required order delivery dates are not random but the result of a heavy planning and optimisation activity that relies on the accuracy of those dates. Material delivered in advance might not find enough space available on truck-unloading, thus requiring (based on the purchasing Incoterms agreements) either the supplier or the manufacturer to pay additional costs for momentarily storing this material. The Delivery Service Index (DSI) mentioned in the previous paragraphs was indeed devised by Whirlpool so as to tackle this issue, obviously penalising less early deliveries than late ones. Such an approach was mandatory in order to match with the DDMRP definition of Daily Qualified Demand (see Chap.2). Finally, a divergent behaviour appears for Throughput where in Sterman the curve presents a smoothed trend delaying the one of Production Starts. In the proposed model the initial behaviour of Throughput trend equals the Daily Production Starts one but it shifted to exactly DLT units from it. This is due to the different delay function used in the proposed model for Throughput than what was done in Sterman. Indeed in the proposed model a *pipeline delay* defined by the DELAY MATERIAL function is used whereas in Sterman a *first-order delay* is used instead. Using a pipeline delay is equivalent to assuming *perfect items dispatching within the stock,* thus goods production is assumed as a rigid, perfect system never affected by variability that always releases the exact amount of requested finished goods after DLT units of time. Such modeller decision was taken to prevent any possible double-countings in the Throughput values once more constraints would be added to Throughput but for sure it represents a *doubtable assumption*.

Evident differences appear instead when comparing the Raw Material Modules responses, as shown in Fig.5.15 and 5.16. Indeed, the biggest differences between the two are yielded by the Supplier Module. While Sterman duplicates its base model so as to have two different companies linked in a supply-chain where purchase orders are exchanged by the downstream company (upon exogenous demand) and smoothed by the upstream supplier, this was not done in the proposed model. As mentioned above, Whirlpool (and typically most companies) does not have visibility on its suppliers data thus it was impossible to have a proper estimate about suppliers inner parameters, required by Sterman model, like the time to update forecast beliefs, to review inventory or issue orders. Those values are company-intrinsic and depend on its management beliefs, thus are typically unknown to its external stakeholders. As introduced above, in the proposed model suppliers consist of a single basic entity which releases all the material requested at once after an agreed delay, without any forecasting and smoothing done by them. For this reason, material deliveries are not as smooth as in Sterman, instead they present typical *Bullwhip oscillations.* This emergent pattern is considered consistent by the author with the conventional supply-chain body of knowledge, moreover this response is similar to what obtained by Sterman further in its model development stages, when trust issues get considered in the model. The same issues are also considered in the proposed model.

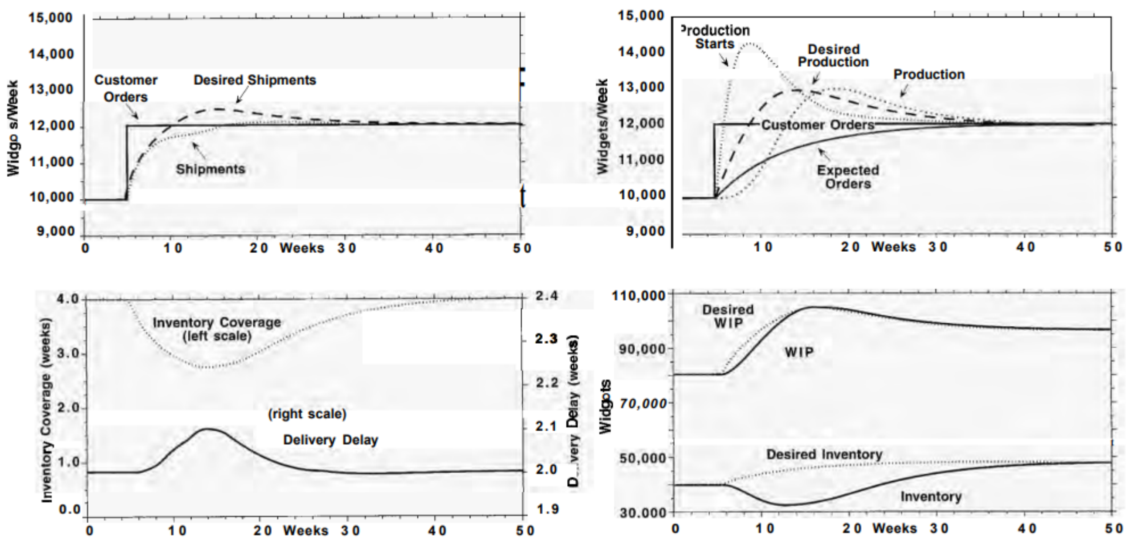
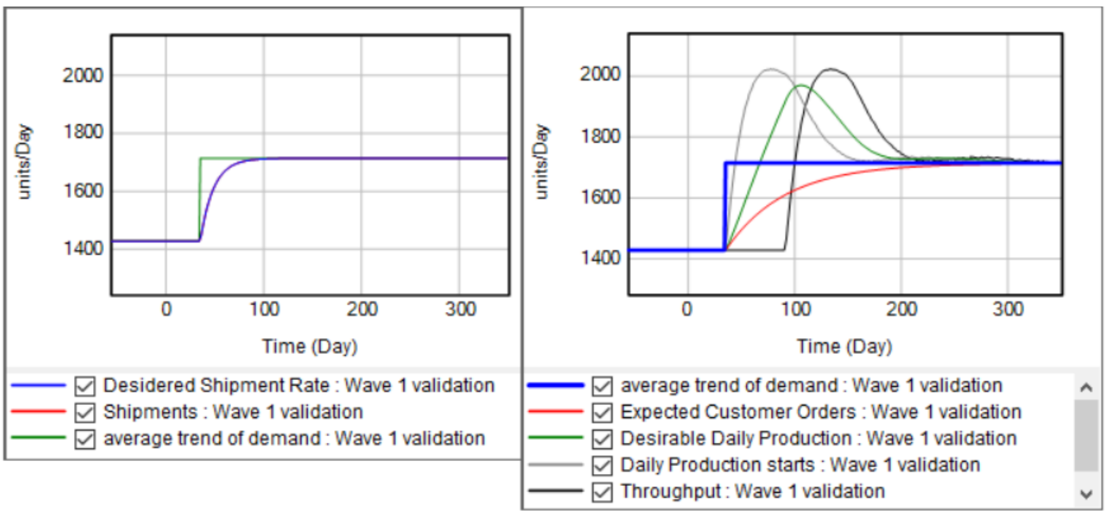


Fig.5.13. *Sterman simulation trends of Finished Good Inventory module after 20% increase in customer orders*



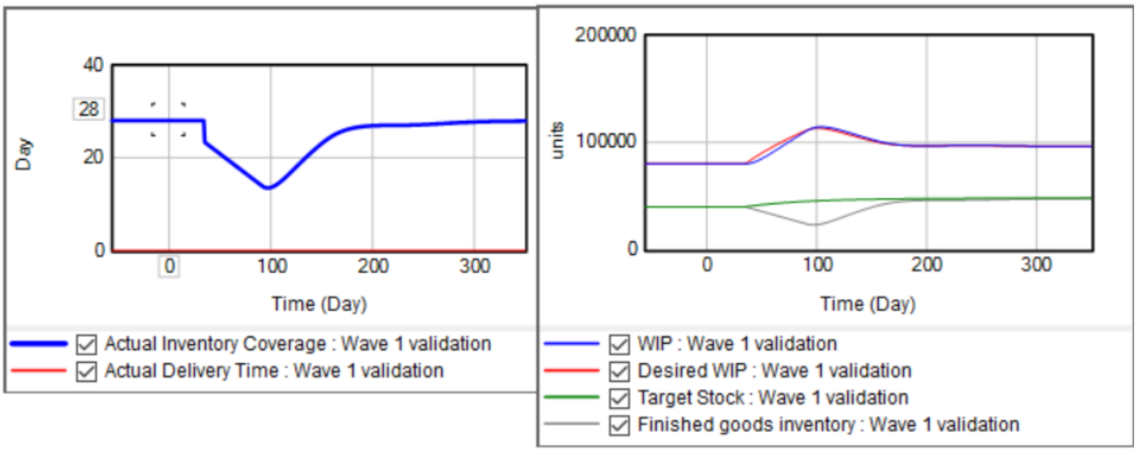


Fig.5.14. *Proposed model Finished goods Inventory trends during validation of WI*

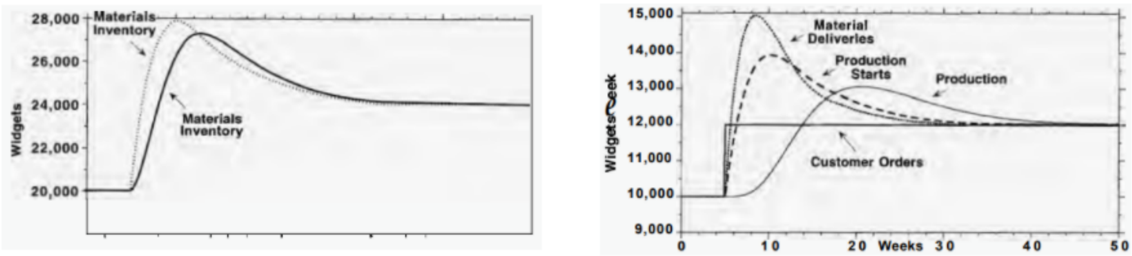
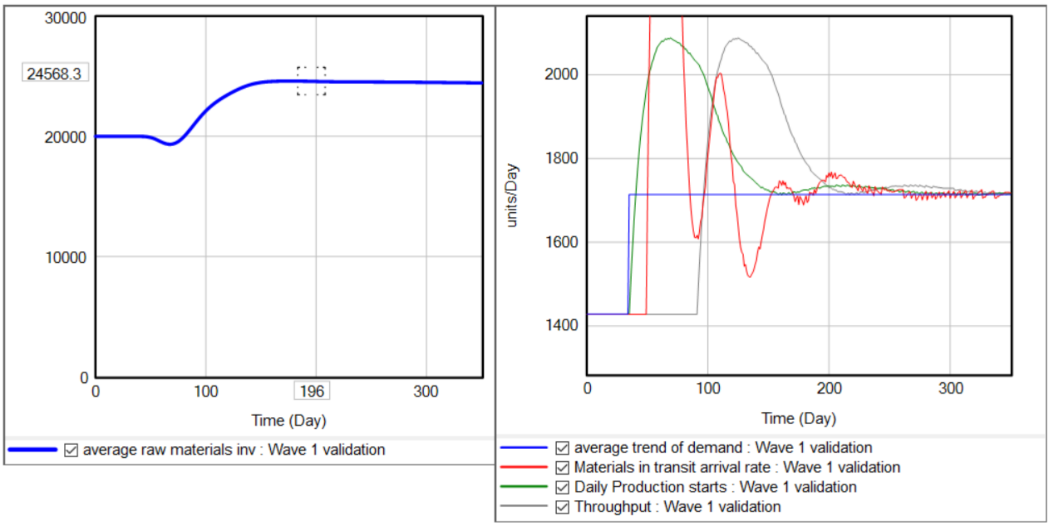


Fig.5.15. *Sterman simulation trends of Finished Good Inventory module after 20% increase in customer orders*



5

Fig.5.16. *Proposed model Raw Materials Inventory trends during validation of WI*

5.3.3. Wave II : Enlarging the base model boundaries

5.3.3.1. Additions to the Finished Goods Inventory Module

5.3.3.1.1. Material Obsolescence

Fig. 5.17 and 5.18 introduce how materials obsolescence is addressed in the Finished Goods and Raw Materials modules. To recall, Whirlpool determination of obsolete goods and material is based on the date of the last recorded good movement in the MSEG SAP transaction. Goods that are not reached by any movement type (e.g. pick-pack and ship, internal reshuffle, production consumption, good returns) for more than 12 months are considered *fully obsolete* and for them the processes of scrapping or reselling can be initiated. This is done by applying a MATERIAL DELAY of 365 days, namely the *Obsolescence Time*, to all the quantities entering the stocks of Finished Goods and Raw Materials. In parallel, a stock *accumulating the information* of all goods moved during the same Obsolescence Time is set so as to be able to compare the potentially obsolete quantities with the total consumed ones. This approach thus implies a FIFO logic to inventory usage.

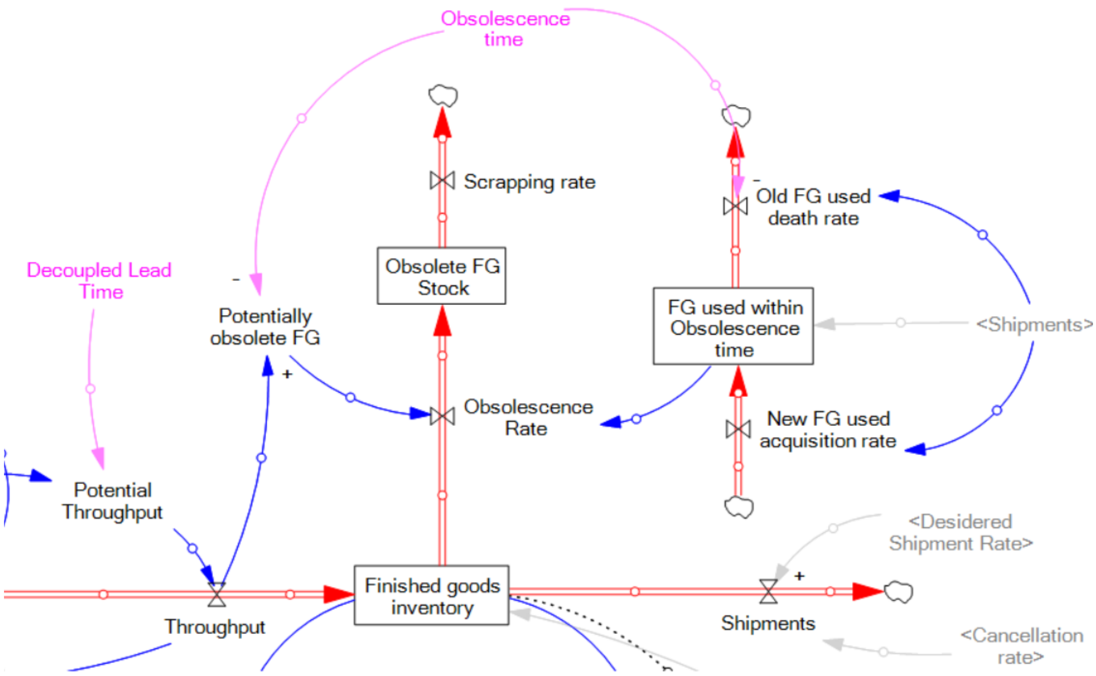


Fig.5.17. *Obsolescence logic in the Finished Goods Module*

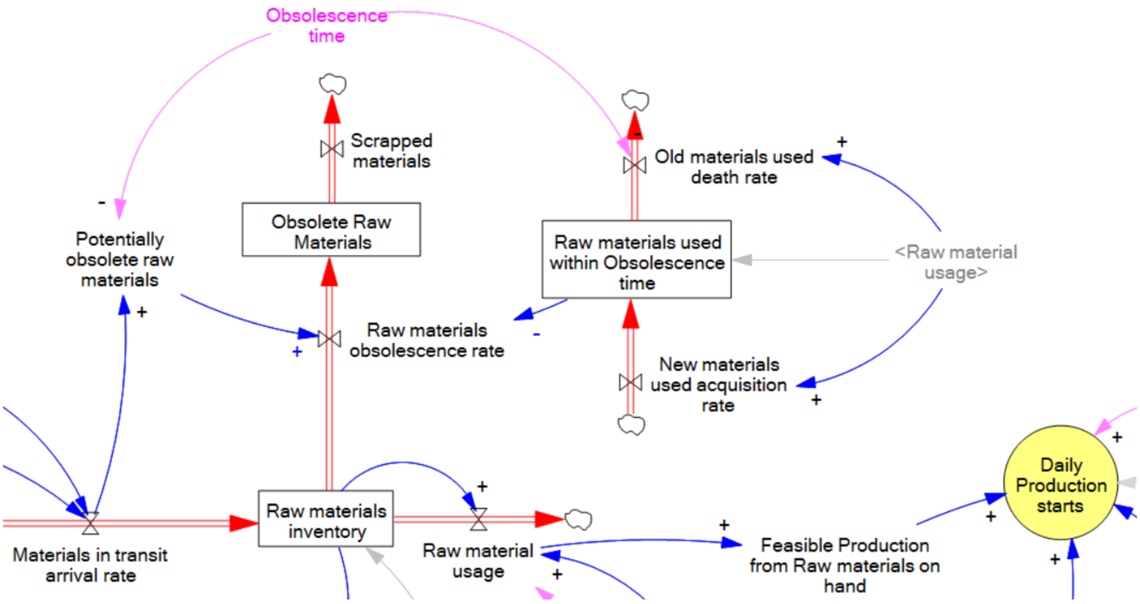


Fig.5.18. *Obsolescence logics in the Raw Materials Module*

As it can be seen, the implementation of obsolescence in either modules is specular. Different variables' names duplicating the same formulations must be created to allow Vensim to discriminate between different flows. Hence, the following formulation of obsolescence is abstracted for any item. The reader can obtain the specific formulation by substituting the relative Item Name in the formulas.

Reformulated ***Items Inventory.***

```
Context = Endogenous          Type = Stock          UOM =
units

Items Inventory = INTEGRAL(Stock Input Flow - Stock Output flow -
Obsolescence Rate, Target Items Inventory)
```

Items Obsolesce Rate. The daily items amount that become obsolete according to the company obsolescence definition (see Chap. 2 for Whirlpool definition of obsolescence).

```
Context = Endogenous          Type = Flow          UOM =
units/day

Obsolesce Rate = MAX(Potentially obsolete items-items used within
Obsolescence time,0)
```

Potentially Obsolete items. The theoretical items amounts that would become obsolete on the current date if they have not been used since first entering the item stock. It represents the Obsolesce Rate upper-bound.

```
Context = Endogenous             Type = Auxiliary      UOM = units/day

Potentially Obsolete items = DELAY MATERIAL(Stock Input Flow,
Obsolescence time, 0, 0)
```

Items used within Obsolescence Time. The accumulation of all items used during a moving time period equal to the Obsolescence Time.

```
Context = Endogenous             Type = Stock                 UOM     =
units

Items used within Obsolescence Time = INTEGRAL(Items used within obs.
input rate-Items used within obs. output rate,  Stock Output flow)
```

Items used within obs. input rate. The items flowing out of the stock at each iteration and that must be added at each iteration to the time-moving sum of used items.

```
Context = Endogenous             Type = Flow                  UOM
=units/day

Items used within obs. input rate = Stock Output Flow
```

Items used within obs. output rate. The used items within obsolescence time quantity that must be subtracted at each iteration from the time-moving sum of used items.

```
Context = Endogenous             Type = Flow                  UOM
=units/day

Items used within obs. output rate = DELAY MATERIAL(Stock Output
flow, Obsolescence time, 0, 0)
```

Obsolete Items. The accumulation of the Obsolescence rate throughout the simulation.

```
Context = Endogenous             Type = Stock                 UOM     =
units

Obsolete Items = INTEGRAL(Obsolescence Rate-Scrapping rate, 0)
```

Obsolescence Time. The company-defined time horizon after which an item that presents no goods movements since then is considered obsolete.

`Context = Exogenous` `Type = Auxiliary` `UOM = day`

Scrapping Rate. The dismantling rate of obsolete items to make them resellable as intermediate components, second-hand material on the spot-markets or as material scraps to shredders.

`Context = Exogenous` `Type = Auxiliary` `UOM = units/day`

It was decided to have this value deactivated by default given that such material reselling dynamics were not included in the current scope of the study.

5.3.3.1.2. Productive Capacity Constraints

To address the RQ3 of this study (see Chap.3), it was of interest to the modeller to evaluate the effects of a capacity bottleneck on different inventory policies. Moreover, assuming an uncapacitated productive system in a model addressed to the operative side, as the one proposed in this study, is a rather strong approximation of reality. To make the addition as impactless as possible on the overall system structure, productive capacity is set exogenously and imposed as a hard bound to the *maximum concurrent WIP* loadable in the system, as shown in Fig.5.19.

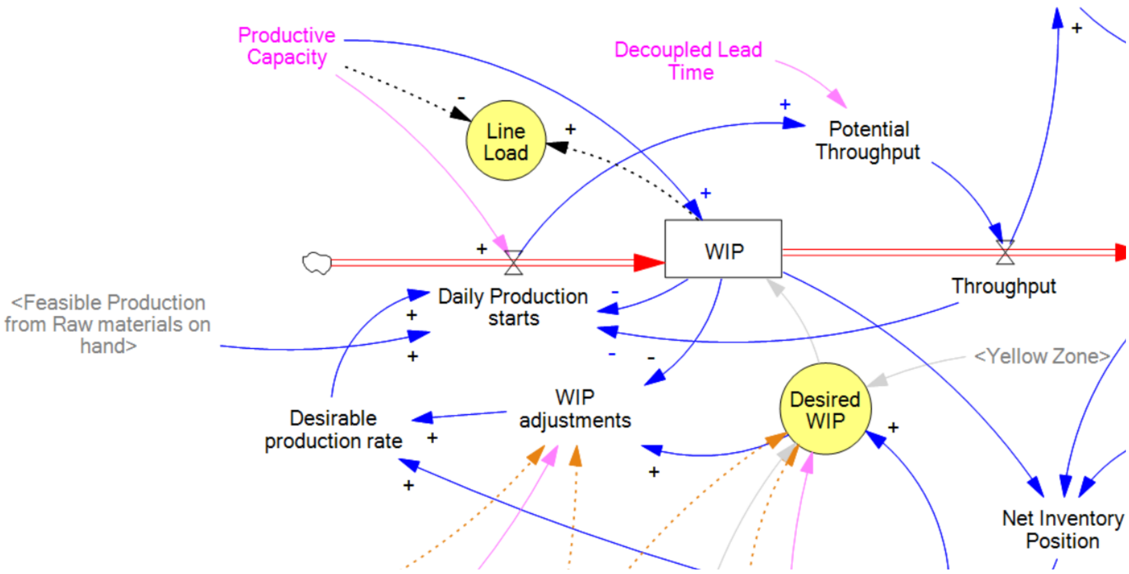


Fig. 5.19. *Addition of the productive capacity constraint to the Daily Production Starts*

Reformulated ***WIP.***

```
Context = Endogenous            Type = Stock              UOM     =
units

WIP   =   INTEGRAL(Daily  Production  starts-Throughput,  MIN(Desired
WIP,Productive Capacity)
```

Productive Capacity. The maximum amount of Work-In-Process that can be loaded on the production environment. It represents the maximum amount of goods the system is capable of generating after a full Manufacturing Cycle Time.

```
Context = Exogenous             Type = Auxiliary      UOM = units
```

Line Load. The fraction of the Productive Capacity saturated by the current state of the WIP.

```
Context = Endogenous            Type = Auxiliary      UOM          =
dimensionless

Line Load = XIDZ(WIP, Productive Capacity, 0)
```

Reformulated ***Daily Production Starts.***

```
Context = Endogenous            Type = Flow               UOM     =
orders/day

Daily Production Starts =
INTEGER(
  MIN
  (
   MIN
     (
      Feasible Production from Raw materials on hand,
      MAX(Desirable production rate, 0)
     ),
   MAX(Productive Capacity-(WIP-Throughput), 0)
 )
)
```

5.3.3.1.3. Quality issues from system overload

Having enlarged the system boundaries to also include productive capacity now allows also to consider all capacity-dependent feedback loops, such as scenarios induced by *overloading conditions*. The modeller assumed that when the productive system is brought up near the maximum limit capacity then the percentage of human mistakes, reworks and machine downtimes would increase. Such a dynamic hypothesis is presented in Fig.5.20. The *WIP scrapping rate* outflow was thus added to the WIP stock to quantify such a material loss.

This quantity reduces the actual throughput from its potential ones, negatively impacting the replenishment capability of the productive system. Thus, a system already struggling in recovering delays rapidly saturates its productive capacity, stressing the system and its workforce to a point where material leaks during production as scraps, increasing the inability to recover delays, closing a "*Schedule Pressure*" balancing feedback loop.

Being the above the result of a modeller's hypothesis that were not fully discussed with Whirlpool GSS analysts, it might possibly induce a bias in the model. Thus, the whole mechanism can be turned on and off. By default the WIP scrapping logic is deactivated in order to prevent potential undetected formulation flaws from interfering during the validation stages.

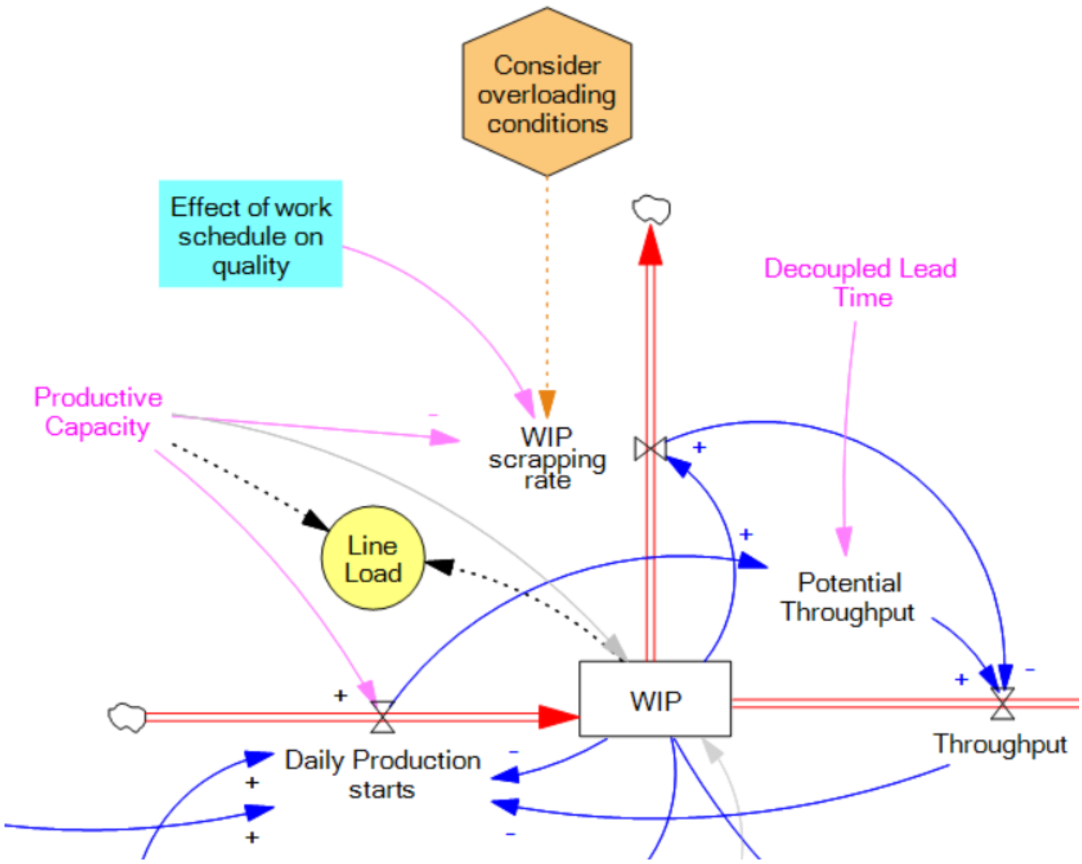


Fig.5.20. *WIP Scrapping rate emerging from an overloaded productive environment*

Consider Overloading conditions. It allows activation of the *Production Overloading scenario* where the effects of peak Line Loads produce part of the scheduled production to be lost as scraps.

```
Context = Exogenous          Type = Scenario      UOM         =
dimensionless
```

Reformulated ***WIP.***

Context = Endogenous Type = Stock UOM = units

WIP = INTEGRAL(Daily Production starts - Throughput-WIP scrapping rate, MIN(Desired WIP, Productive Capacity))

WIP scrapping rate. The amount of WIP that is lost due to accidents during production, machine breakages or human mistakes induced by a busy productive environment reaching its peak throughput.

```
Context = Endogenous            Type = Flow          UOM = units/day
```

```
WIP scrapping rate = IF THEN ELSE(Consider overloading conditions=1,
INTEGER(Effect of work schedule on quality(XIDZ(WIP,Productive
Capacity, 0))*WIP), 0)
```

Effect of Work schedule on quality. The percentage of scraps generated by the production system as a function of the actual Line Load.

```
Context = Endogenous            Type = Lookup        UOM
=dimensionless
```

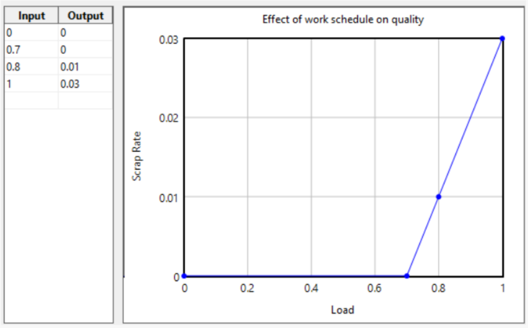


Fig. 5.21. *Lookup for the Effect of Work Schedule on Quality*

Reformulated ***Throughput.***

```
Context = Endogenous            Type = Flow          UOM          =
orders/day
```

```
Throughput =  MAX(Potential Throughput-WIP scrapping rate, 0)
```

5.3.3.2. Adding Order cancellations

In the proposed model all backorders affected by Delivery Delays greater than the Customer Tolerance Time are assumed lost, as explained in Par. 5.3.1.5 and 5.3.1.6. Upon this assumption, Fig. 5.22 presents the implementation of the rule in SD. By a quick look it can be seen that a similar approach used for modelling material obsolescence was exploited. In essence, at each iteration the Potentially Due Orders are compared with the Orders fulfilled within CTT stock. If the latter is smaller than the previous then some orders were not met during the CTT and therefore will be cancelled *when the customer recognizes the order is in delay* thus *on the day after its promised delivery date*.

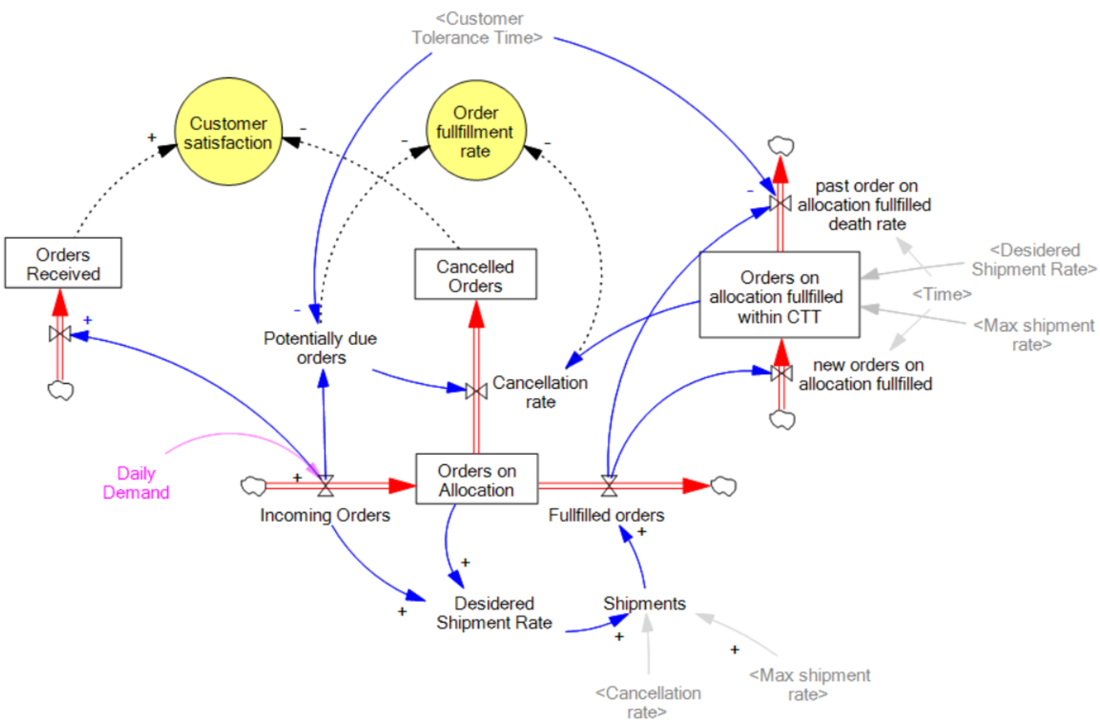


Fig.5.23. *Order Cancellation logic addition to the base Order Fulfilment Module*

Reformulated ***Orders On-allocation.***

`Context = Endogenous          Type =Stock          UOM = orders`

`Orders On-allocation = Incoming Orders-Cancellation rate - Fulfilled orders`

Cancellation Rate. The daily cancelled orders.

`Context = Endogenous          Type = Flow          UOM = orders/day`

```
Cancellation Rate = MAX(Potentially due orders -Orders Fulfilled
within CTT, 0)
```

Potentially Due Orders. The theoretical amount of daily orders that would be cancelled on current date if they suffered a delivery delay greater than the CTT. Customers wait the day after the order's promised date before cancelling the order.

```
Context = Endogenous          Type = Auxiliary      UOM          =
orders/day

Potentially Due Orders = DELAY MATERIAL(Incoming Orders, Customer
Tolerance Time+1, 0, 0)
```

Orders fulfilled within CTT. The accumulation of fulfilled orders during a moving period equal to the CTT.

```
Context = Endogenous          Type = Stock          UOM = orders

Orders fulfilled within CTT = INTEGRAL(Orders fulfilled within CTT
input rate.-Orders fulfilled within CTT output rate, 0))
```

Orders fulfilled within CTT input rate. The new daily fulfilled orders flowing out Orders On-Allocation stock that must be added at each iteration to the time-moving sum of fulfilled orders within CTT.

```
Context = Endogenous          Type = Flow           UOM          =
orders/day

Orders fulfilled within CTT input rate = Fulfilled orders
```

Orders fulfilled within CTT output rate. The daily fulfilled orders that must be subtracted at each iteration to the time-moving sum of fulfilled orders within CTT.

```
Context = Endogenous          Type = Flow           UOM          =
orders/day

Orders fulfilled within CTT output rate = DELAY MATERIAL(Fulfilled
orders, Customer Tolerance Time, 0, 0)
```

Cancelled Orders. The accumulation of the Cancellation Rate throughout the simulation.

```
Context = Endogenous          Type = Stock          UOM = orders

Cancelled Orders = INTEGRAL(Cancellation Rate, 0)
```

Order Fulfilment Ratio. The fulfilled fraction of the daily due orders. An assumption of the proposed model formulation is indeed that orders can be fulfilled also by single units, even if a customer might request a batch order of multiple units.

```
Context = Endogenous              Type = KPI      UOM = dimensionless

Order Fulfilment Ratio = 1-XIDZ(Cancellation rate, Potentially due
orders, 0)
```

Customer Satisfaction. The fraction of satisfied customers during the entire simulation.

```
Context = Endogenous              Type = KPI      UOM = orders/day.

Customer Satisfaction = 1-XIDZ(Cancelled Orders, Orders Received, 0)
```

Order Received. The accumulation of all orders received during the simulation.

```
Context = Endogenous              Type =Stock           UOM = orders

Order Received = INTEGRAL(Incoming Orders,0)
```

5.3.4. Validating Wave II : Model response under extreme testing conditions

5.3.4.1. Testing conditions

In sight of the additions done to the model in Par. 5.3.2, *the scope of this validation phase is less about reproducing known data and more on "stress-testing" the model* so as to let potential issues emerge. Moreover, the customisations introduced to the base Order Fulfilment Model are tested for resilience against possible infringements of the basic physic law of mass conservation.

Fig. 5.23 shows the input stimulus used for this validation phase: a base sinusoidal function is given as input to a *random pink noise generator* producing 5-days (e.g. one working week) autocorrelated values. Exact formulation of the sinusoid used to generate the average input trend is provided in Par. 5.3.1.4. The simulation will last 365 days.

$Average\ Trend\ of\ Demand\ =\ Sinusoidal\ Demand \qquad (see\ Par.\ 5.3.1.4)$

```
Demand Trend =
INTEGER(
 IF THEN ELSE(realistic demand=1,
  MAX(RANDOM PINK NOISE(Average Trend of Demand,0.2*Average
Trend of Demand, 5, 0), 0),
```

```
 Average Trend of Demand)
)
```

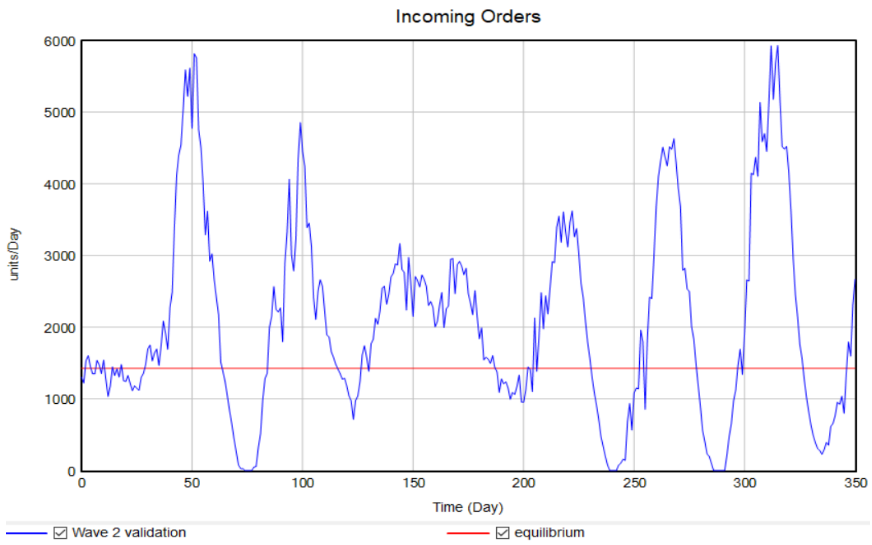


Fig.5.23. *Damped sinusoidal perturbation from equilibrium condition in Customer Orders*

To make the validation working environment as complex as possible to the model, additional constraints are added to face such an high variable demand trend, namely

Capacity Bottleneck. Productive capacity is cut to only 120.000 pcs of concurrent production in WIP,

$$Max\,Throughput = \frac{Productive\ Capacity}{Manufacturing\ Lead\ Time} = \frac{120.000\ pcs}{56\ day} \approx 2150\ pcs\ /\ day \quad ;$$

$$E(Demand\ Input) = \mu_D = 2680\ \frac{pcs}{day} > Max\,Throughput \quad ;$$

$$STD.DEV(Demand\ Input) = \sigma_D = 1468.40\ \frac{pcs}{day}$$

"Fast-fashion" Industry. Customers are willing to wait only 1 day (CTT=1) before cancelling their orders.

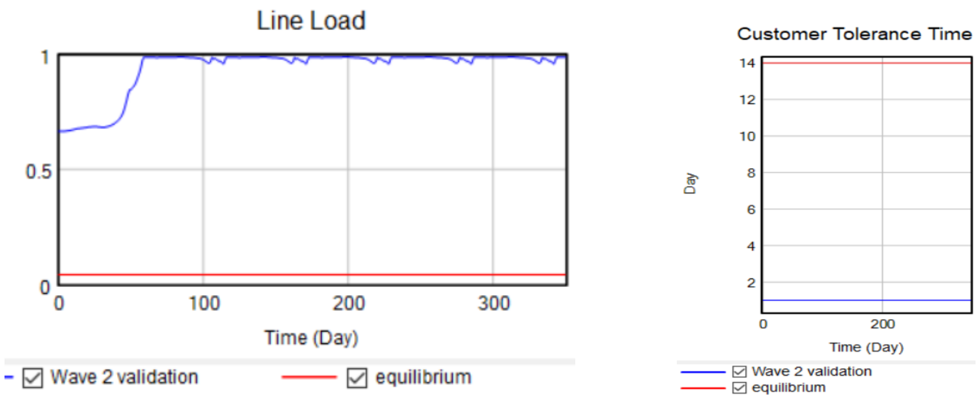


Fig. 5.24. *Harsh limiting boundary conditions during validation of W-II*

All other model parameters were left unchanged as set during the validation phase of W-I, as listed in Tab. 5.3. The model response to these working conditions is instead presented in Fig. 5.25, 5.26, 5.27 and 5.28.

Finished Good Inventory parameter	**Validation W.II**	**Raw Materials Inventory parameter**	**Validation W.II**	**Demand Forecasting Module parameter**	**Validation W.II**
Productive Capacity	120.000 pcs	Avg BOM parent to child usage ratio	1 pcs/pcs	*Customer Orders*	See Fig. 5.23
Decoupled Lead Time	56 days	Raw Materials Safety Stock Coverage	6 days	*Time to perceive orders rate changes*	56 days
FG Inventory adjustment time	56 days	Raw Materials Inventory Review Period	14 days	**Order Fulfilment Module parameter**	**Validation W.II**
WIP adjustment time	14 days	Order Release Time	14 days	*Customer Tolerance Time*	1 days
WIP scraps rate	0 pcs/day	Agreed Purchasing Lead Time	7 days		
Obsolescence Time	365 days	*Obsolescence Time*	365 days		
Finished Goods Safety Stock Coverage	14 days				

Tab.5.3. *Parameters setting for validating W-II*

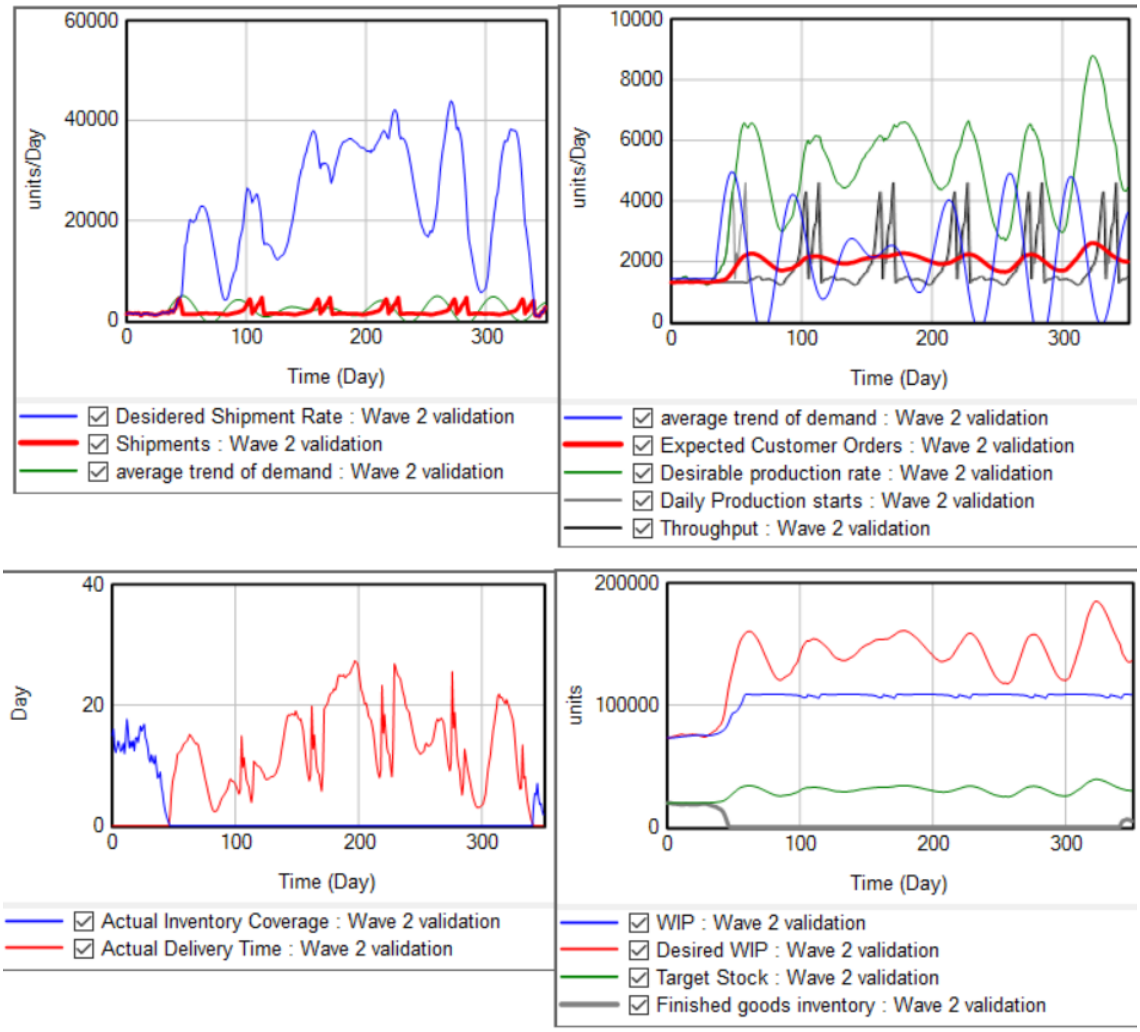


Fig.5.25. *Finished goods Inventory module performances under extreme testing condition*

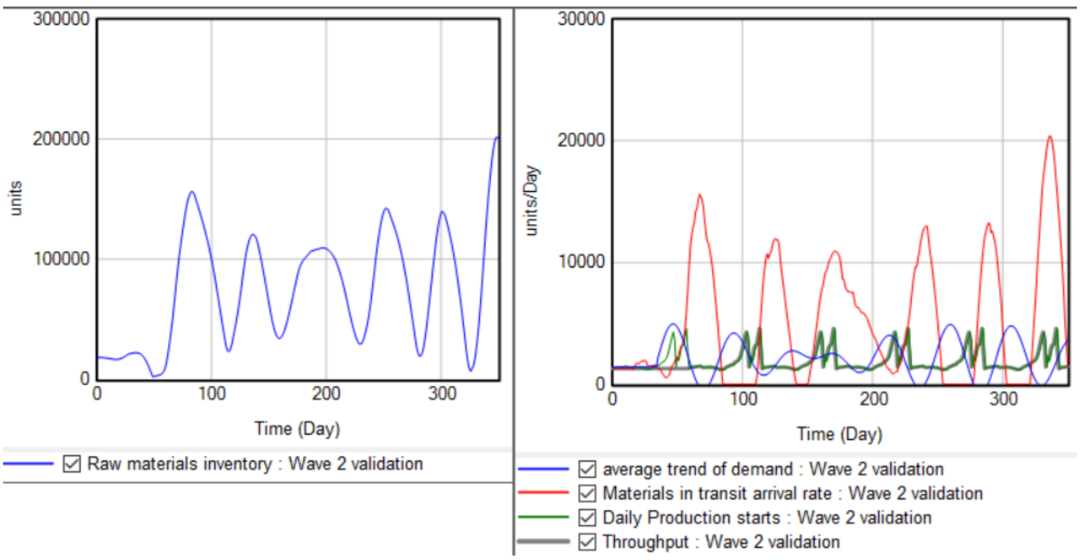


Fig.5.26. *Raw Materials Inventory trends under extreme testing condition*

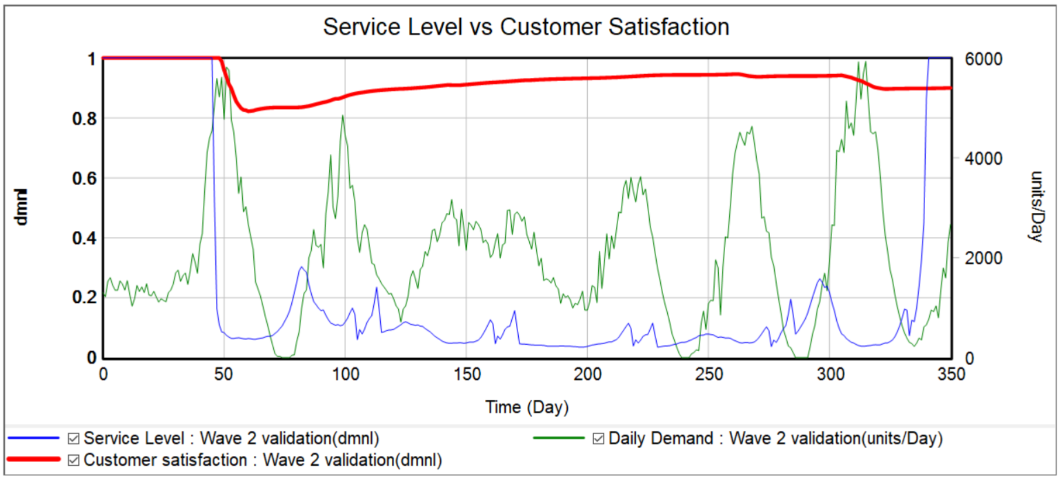


Fig.5.27. *Service Levels and Customer Satisfaction versus the input signal under extreme testing condition*

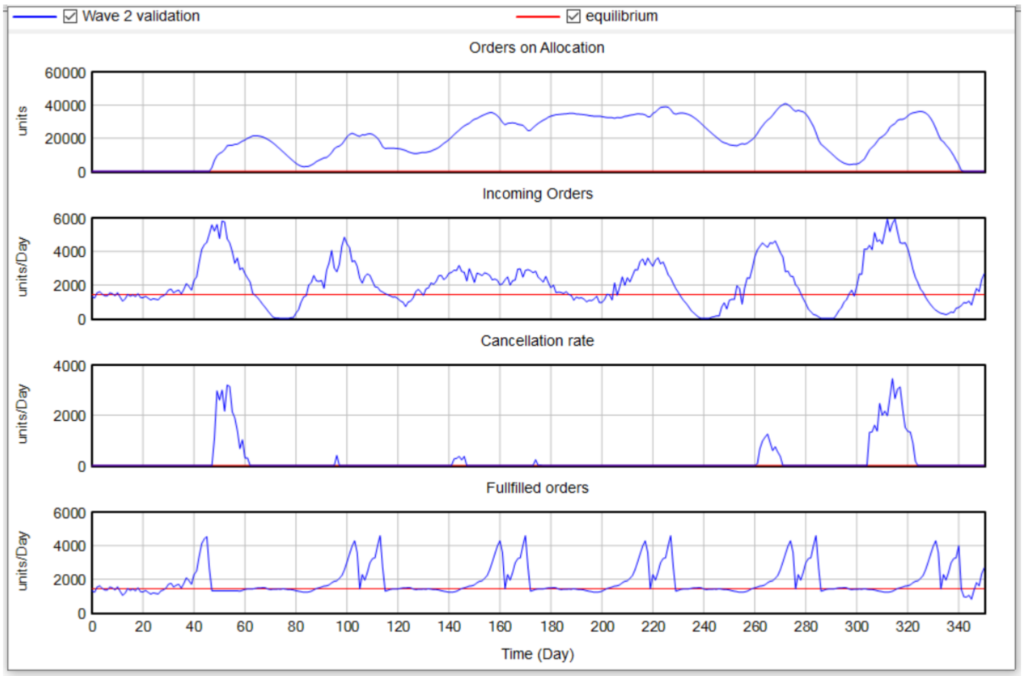


Fig.5.28. *Order Fulfilment module performances under extreme testing condition*

5.3.4.2. Discussion of the model response

The system struggled dealing with such a demand signal, *never recovering Service Level* over 20% *neigher during periods of decreasing demand*. On the other hand, *the company seems able to maintain and surprisingly gain customer satisfaction even while maintaining very low service levels.* However, such behaviour should be doubted.

Regarding the Actual Delivery Time, which during the validation of W-I always stayed to 0, it increased as soon as the Finished Good Inventory reached no coverage as expected. Surprisingly instead, **the frequency of order cancellations stayed quite low** regardless of the harsh condition the company was facing. By intuition, *as soon as the Actual Delivery Time overshoots the Customer Tolerance Time the amount of cancelled orders should rise*.

Finally, some remarks regarding capacity bottlenecking emerged after the CTT was allowed to increase from the initial condition set (CTT = 1) for this validation phase. As intuiable, in all runs the general system response was mainly driven by the productive capacity bottleneck. The Line Load trend repeats after each manufacturing cycle completes.

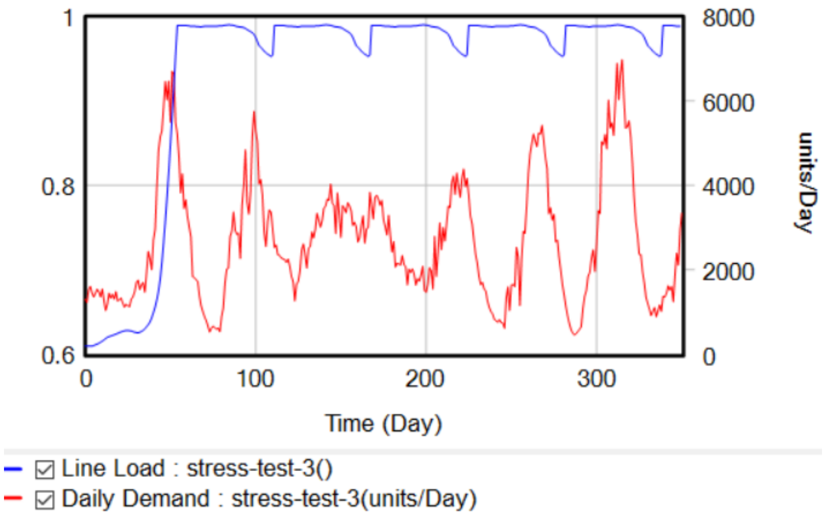
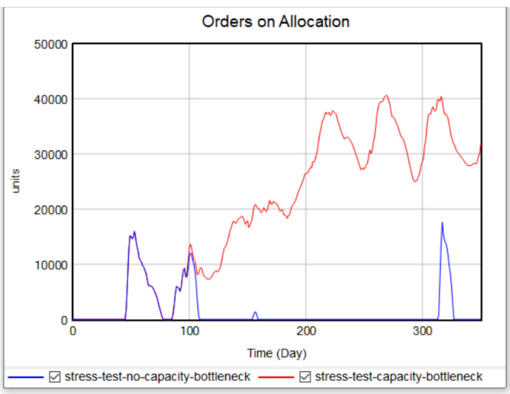


Fig. 5.29. *The capacity bottleneck constraining order fulfilment module during the entire simulation*

By analysing the model response under different CTTs settings (CTT>1), results suggest that *when a capacity bottleneck is introduced, the system throughput is not large enough to replenish the inventory faster than daily shipment withdrawals*. Thus, once the equilibrium quantity stocked in inventory at the beginning of the simulation is fully consumed, the actual shipment rate must equal the throughput rate. In this scenario, it occurs that *the orders on-allocation grow indefinitely at a rate proportional to the daily unsatisfiable portion of incoming orders.*



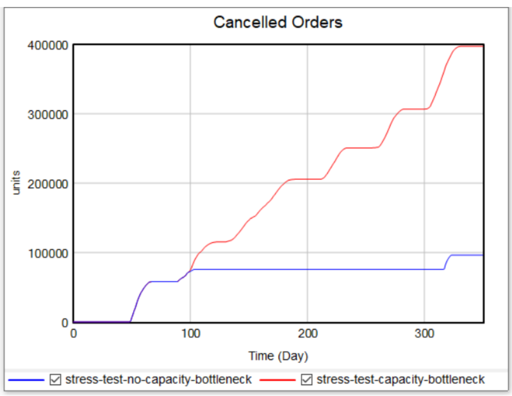


Fig.5.30. *Effects of a capacity bottleneck on Orders On-Allocations and Cancelled Orders. Max capacity in red = 70.000 pcs; Max capacity in blue = 200.000 pcs; CTT = 3 days.*

In general, as seen in Chap.4, *no quantity can really grow indefinitely*, thus the ones that do typically highlight potential issues in the model formulation.

An extensive testing session was thus run in order to spot formulation flaws emerging from all the aforementioned issues and led to the following conclusions

(1) **A growth behaviour of backorders is the only one attainable in presence of a capacity bottleneck** under the current model formulation. Indeed, a base assumption of the proposed model is that orders can be partially fulfilled even by single units. Thus, *a bottlenecked system is only capable of at least satisfying the order fraction covered by its maximum throughput*. The unfulfilled remaining units of a Potentially Due Order will be cancelled if stationary in the stock for longer than CTT. However, even in the worst case scenario (e.g. throughput=0, CTT=0) *the maximum quantity cancelled cannot be greater than the initial order*, thus at best keeping the stock of orders on allocation in equilibrium at the specific level it sits at that moment. In other words, **the system will be capable of lowering its backorders stock only when there is unused capacity**, such as during periods of decreasing demand, where multiple waiting orders can be processed at once, letting the Order Fulfilment Rate overshoot the Daily Demand. That is what indeed happens when Productive Capacity is not constraining the system in Fig. 5.31.

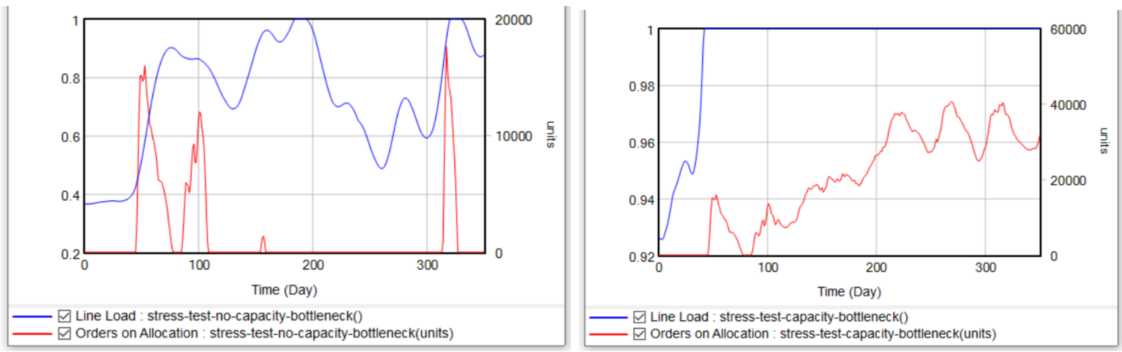


Fig.5.31. *Backorders accumulate only in presence of a productive capacity bottleneck*

(2) **a bias was introduced in the Order Cancellation logic**,

(3) **a double-counting issue was included in the computation of cancelled orders**, artificially lowering the cancellation rate,

(4) **an imprecise formulation for the Actual Delivery Time was used**, and

(5) **an imprecise definition of the Service Level was used**.

These insights emerging from the initial model response *obliged the modeller to review the whole order cancellation logic*.

5.3.4.3. Model Reformulation

5.3.4.3.1. Unbiased Order Cancellation logic

Comparing Actual Delivery Time and Order Cancellations side-by-side produced the trends presented in Fig. 5.32. The system response does not match with intuition. While the Actual Delivery Time continues growing, peaking to around 30-days (30x the Customer Tolerance Time) at t=200, yet we see no orders cancellations.

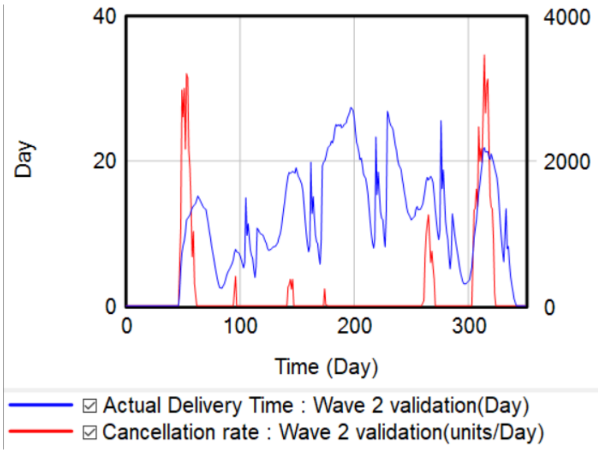


Fig.5.32. *Actual Delivery Times versus Order cancellations affected by a bias*

As shown in Par. 5.3.2.1.3, the author initially set order cancellations to occur only after 1 time-unit had passed since the Customer Tolerance Time expiration. Such *personal bias* **allowed the company to virtually have an additional day available to satisfy those late deliveries** thus improving the order cancellation metric. Indeed, if unlabeled in Fig. 5.32, the two trends would seem rather unrelated. Once removed the bias, thus *letting orders getting cancelled after exactly CTT-time units*, a re-run under the same conditions produced the trends in Fig. 5.33. As it can be seen, the two trends now "follow each other" (being however plotted on different scales) almost perfectly: as soon as the Actual Delivery Time is greater than CTT, order cancellations start occuring. By applying such a small change, the new response of the system changed substantially, as shown by Fig. 5.34 and Fig.5.35.

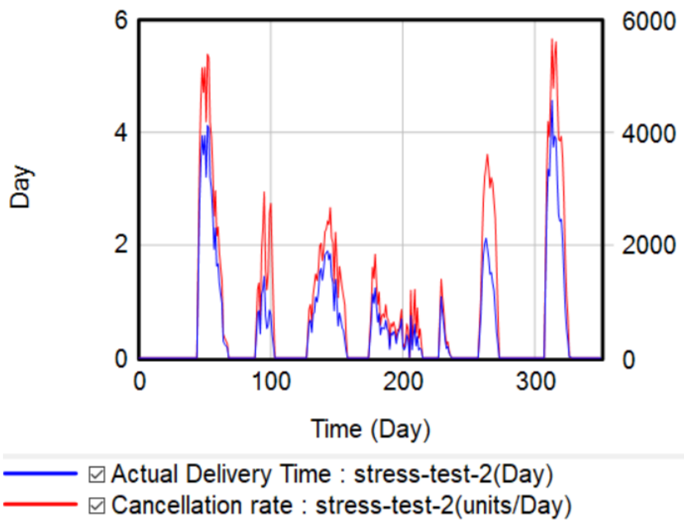


Fig.5.33. *Actual Delivery Time versus Order cancellations under extreme testing condition after W-II reformulation*

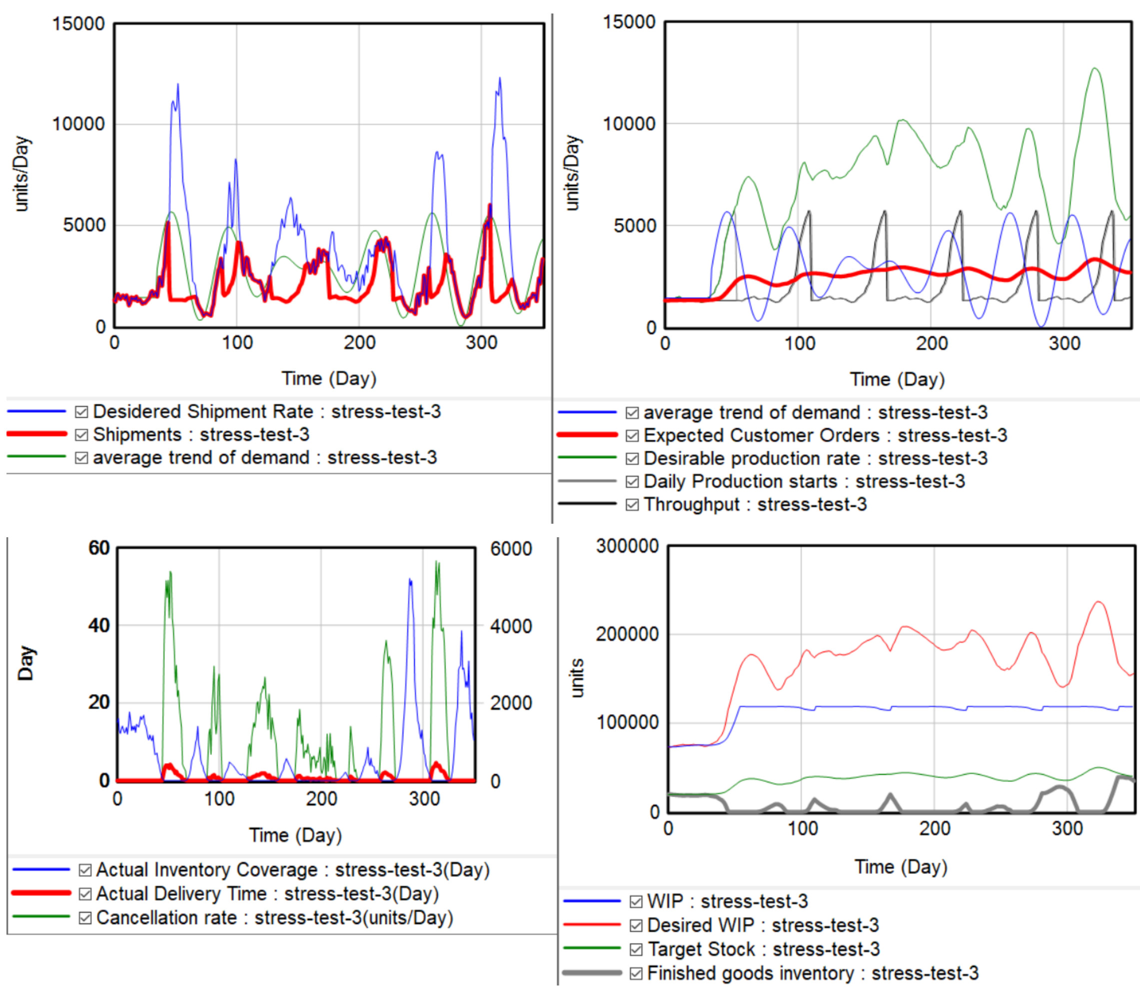


Fig.5.34. *Finished goods Inventory module performances under extreme testing condition after W-II model reformulation*

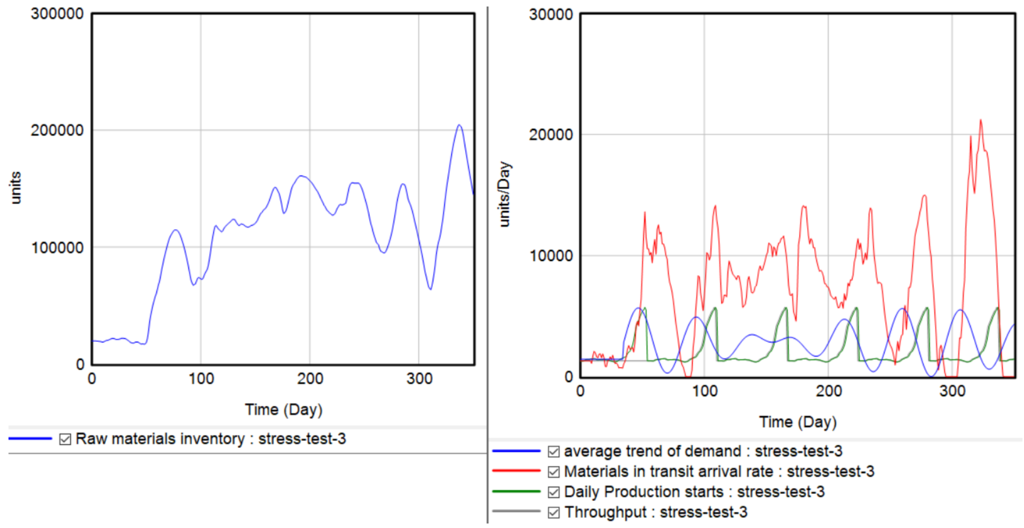


Fig. 5.35. *Raw Materials Inventory module performances under extreme testing condition after W-II model reformulation*

Another positive behaviour is presented in Fig. 5.36 where *Service Level reasonably presents valleys where demand instead peaks*. Being the production centre constantly saturated by new production orders (Fig. 5.29), *is rather likely to expect a reduction in Service Levels if orders rises than an increase*. In the previous model formulation the situation was instead reversed, with service levels picking where demand picked, even if being stuck to very low values.

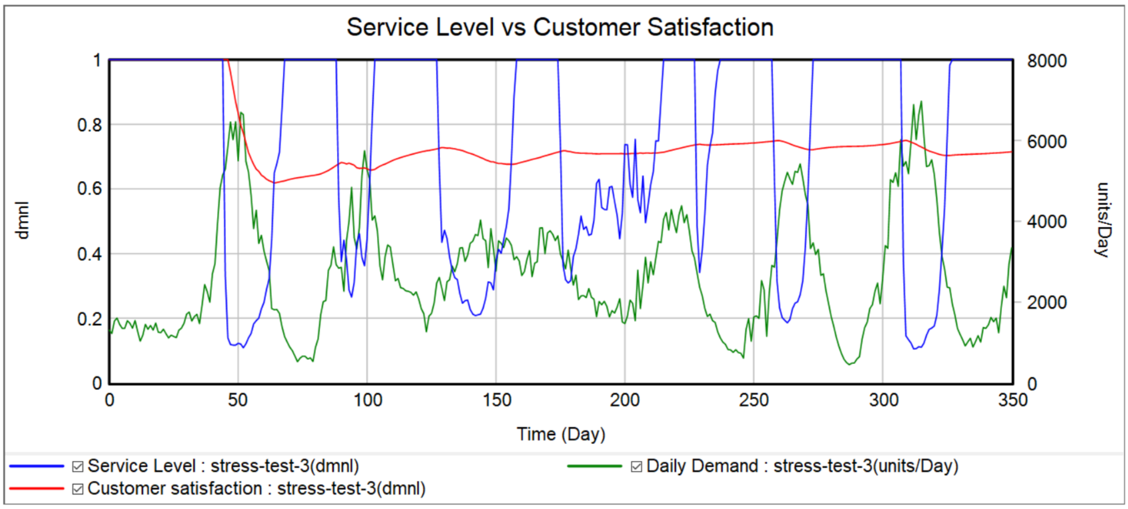


Fig. 5.36. *Service Level and Customer Satisfaction under extreme testing condition after W-II model reformulation*

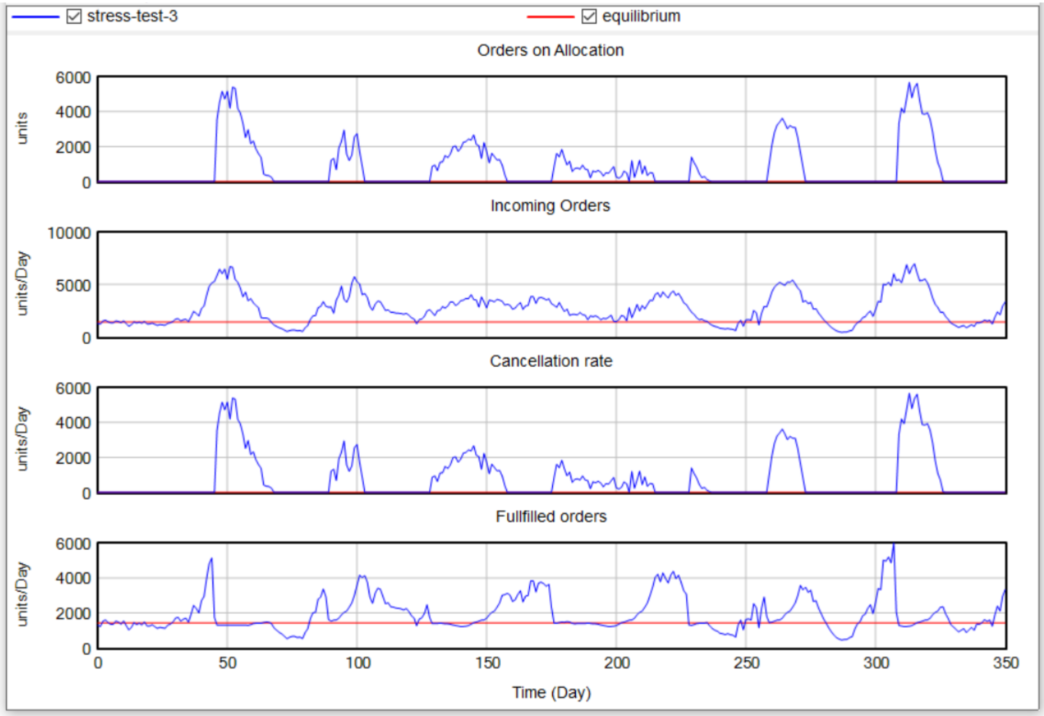


Fig.5.37. *Order Fulfilment module performances under extreme testing condition after W-II model reformulation*

5.3.4.3.2. Inflated Order Cancellations and Schedule Gains

Once removed the initial bias, it was noticed that the former formulation to compute the Cancellation Rate was not netting the total quantity of satisfied orders within CTT with the ones used to satisfy the daily due order. Consider the following example where a constant order input of 2900 pcs/day is required to a system with maximum throughput of 1400 pcs / day, allowing 2 days of CTT. As can be seen by Tab. 5.4, the former formulation of the Cancellation Rate used to doubly assign accumulated production within CTT to two consecutive Potentially Due Orders, artificially understating the amount of Orders Cancellations.

Time	Daily Thorughput	Orders fullfilled w/in CTT	Due orders	Schedule Gains	Daily Fullfilment Capacity	Cancellation Rate (new)	Cancellation Rate (old)
0	1400.00	0.00	0.00	0.00	1400.00	0.00	0.00
1	1400.00	1400.00	0.00	1400.00	1400.00	0.00	0.00
2	1400.00	2800.00	2900.00	0.00	2800.00	100.00	100.00
3	1400.00	2800.00	2900.00	0.00	1400.00	1500.00	100.00
4	1400.00	2800.00	2900.00	0.00	1400.00	1500.00	100.00
5	1400.00	2800.00	2900.00	0.00	1400.00	1500.00	100.00
6	1400.00	2800.00	2900.00	0.00	1400.00	1500.00	100.00
7	1400.00	2800.00	2900.00	0.00	1400.00	1500.00	100.00
8	1400.00	2800.00	2900.00	0.00	1400.00	1500.00	100.00

Tab. 5.4. *Original formulation of Cancellation Rate compared with the reformulated one*

The new concept of *Schedule Gains* was thus introduced to the Order Fulfilment Module. Fig 5. 38 shows the modification done to the model so as to include Schedule Gains.

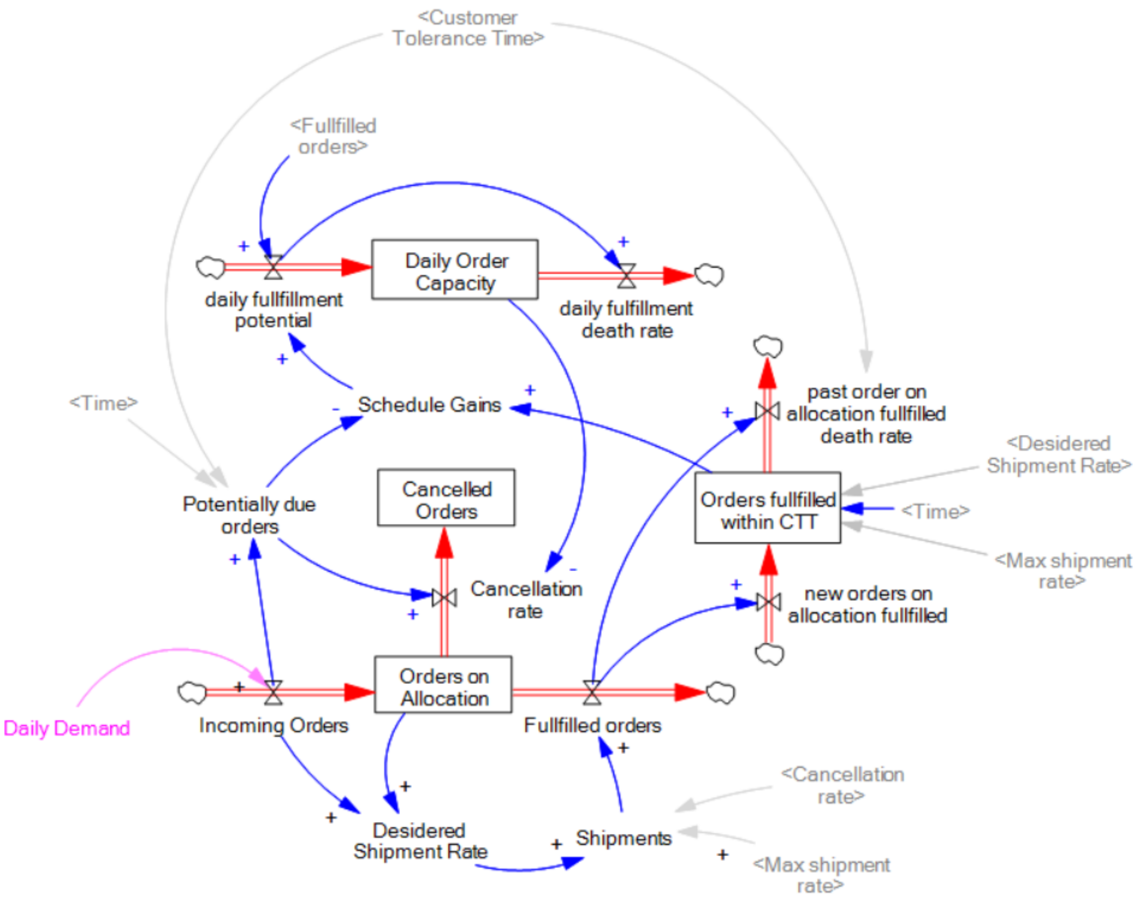


Fig.5.38. *Modifications to the Order Fulfilment Module to implement corrected Cancellation Rate Formulation*

Schedule Gains. The quantities available, among what produced since the beginning of the current CTT cycle, to fulfil tomorrow Potential Due Orders in addition to the daily Throughput.

```
Context = Endogenous          Type = Auxiliary     UOM          =
orders/day.

Schedule Gains   = DELAY MATERIAL(MAX(Orders Fulfilled within CTT -
Potentially Due Orders ,0), 1, 0, 0)
```

To prevent circularity issues by means of *initial simultaneous equations* between Fulfilled Order Rate and the Cancellation Rate, it was mandatory to let Schedule Gains and daily Throughput accumulate in a stock called ***Order Fulfilment Capacity***.

```
Context = Endogenous          Type = Stock          UOM = orders
```

```
Order Fulfilment Capacity = INTEGRAL(Order Fulfilment Capacity inp.
Rate - Order Fulfilment Capacity out. Rate., 0)
```

Order Fulfilment Capacity inp. Rate. The daily capacity of the system to satisfy the Potentially Due Order.

```
Context = Endogenous          Type = Stock          UOM = orders

Order Fulfilment Capacity inp. Rate= Schedule Gains + Throughput
```

Order Fulfilment Capacity out. Rate. The Order Fulfilment Capacity value that must be subtracted from the Order Fulfilment Capacity stock to prevent double countings.

```
Context = Endogenous          Type = Stock          UOM = orders

Order Fulfilment Capacity out. Rate = DELAY MATERIAL(Order Fulfilment
Capacity inp. rate, 1, 0,0)
```

Reformulated ***Cancellation Rate.***

```
Context = Endogenous          Type =Flow      UOM = orders/day.

Cancellation Rate = MIN(MAX(Potentially due orders-Daily Order
Capacity,0), Orders on Allocation)
```

5.3.4.3.3. Actual Delivery Time and Time to Fulfil Shortages

By reviewing the whole Order Fulfilment Module in the previous points, it was noticed that the initial Actual Delivery Time formulation, a heritage of the Sterman base model, did not really represent in the proposed model the same concept intended by Sterman. Indeed, in its initial formulation the Actual Delivery Time was defined as

Actual Delivery Time = INTEGER(XIDZ(Orders on Allocation, Fulfilled orders), 1)) ;

However, this formulation does not provide a proper estimate of what the variable was meant to be in the proposed model, rather it provides *the time required by the system to get rid of all the backorders given the actual fulfilment rate*. Thus, it was decided to separate the two concepts, being both equally important in providing a more complete view on the system state. Interestingly, the changes introduced to address the the previous points turned out to be exploitable to also provide a proper formulation for the Actual Delivery Time *on a per-order basis*

Reformulated **Actual Delivery Time**. The actual time to order delivery yielded by the system.

```
Context = Endogenous              Type = Auxiliary      UOM = days

Actual Delivery Time =
 MAX
 (
  Customer Tolerance Time *
   (1 + (1 - Order Fulfilment Ratio) - XIDZ(Schedule Gains, Orders
received within CTT, 0)),
  0
 )
```

The logic behind the above formulation is that *orders can be either fulfilled within the CTT or not.*

If they are not, then it means that part of them will be cancelled, lowering the Order Fulfilment Rate. The cancelled amounts can be used as a *proxy estimate* for "how much the initial order was in delay". Hence, *the inverse of the Order Fulfilment Ratio provides the first CTT adjustment factor to increase it* so as to estimate what the real delivery time would have been if the company was to ship the full order under the base Sterman model formulation; whereas

If they are, then the system must have accumulated a certain total schedule gain so far and it is highly likely that the current order will be fulfilled either the same day, or at worst, within less than CTT. Hence, *the Schedule Gain, distributed on all Orders Fulfilled within CTT, provides the second adjustment factor for CTT to reduce it* so as to measure the anticipated response of the company.

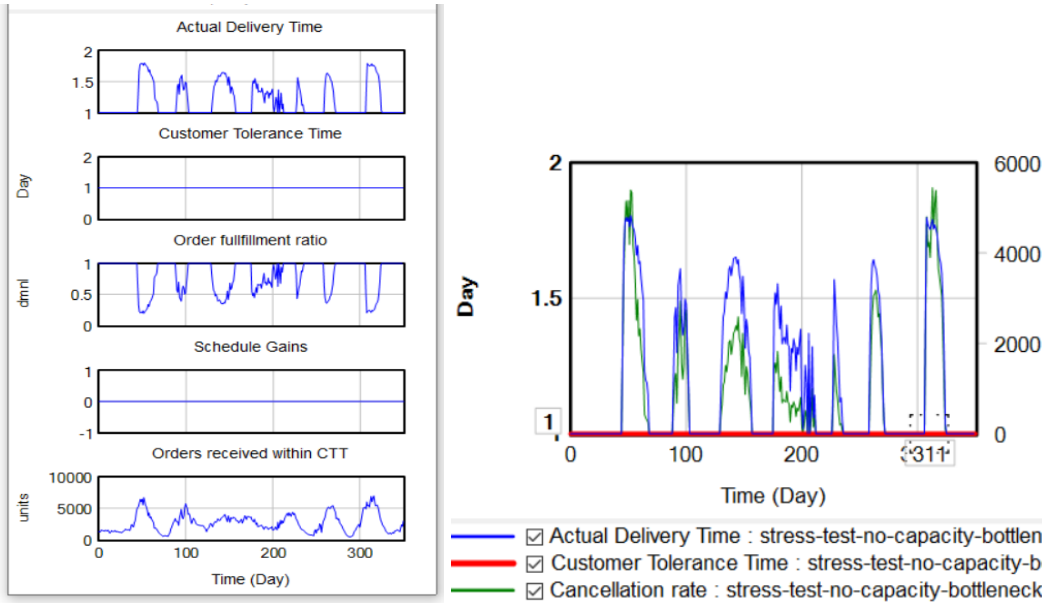


Fig.5.39. *Actual Delivery Time response under the initial extreme testing condition after W2 model reformulation*

Is worth noticing that the reformulated Actual Delivery Time reproduces a comparable trend with the one in Fig. 5.33, morbidly validating its correctness. However, it is also worth noticing that the trend in Fig. 5.33 only occurs as a special case of CTT = 1 under the former Actual Delivery Time formulation, whereas the current one *generalises for any CTT*. Fig. 5.40 shows such lack of consistency of the previous Actual Delivery Time formulation where when CTT > 1 the Actual Delivery Time is rather measuring the **Time to Fulfil Shortages**.

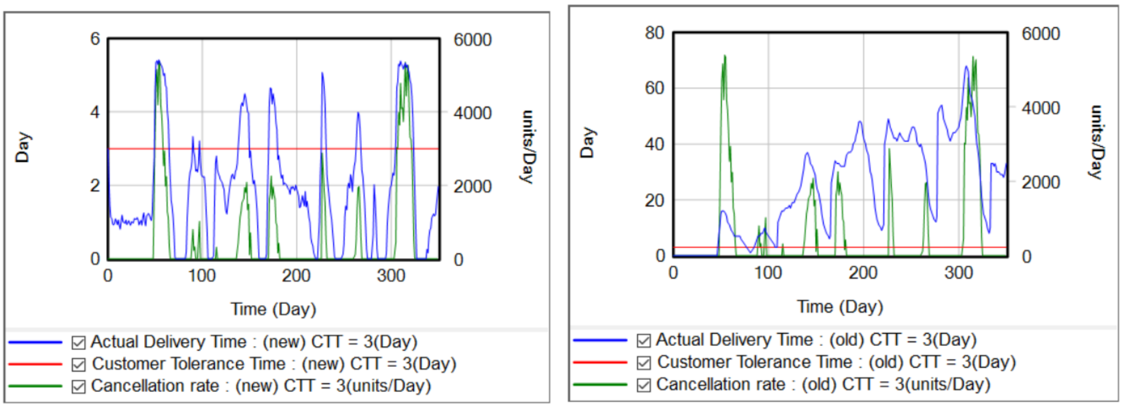


Fig.5.40. *Former incoherent formulation of Actual Delivery Time versus the reformulated one under the extreme testing conditions*

Thus, those metrics were separated and captured in the proposed model by renaming the old Actual Delivery Time into Time to Fulfil Shortages, as shown in Fig.5.41.

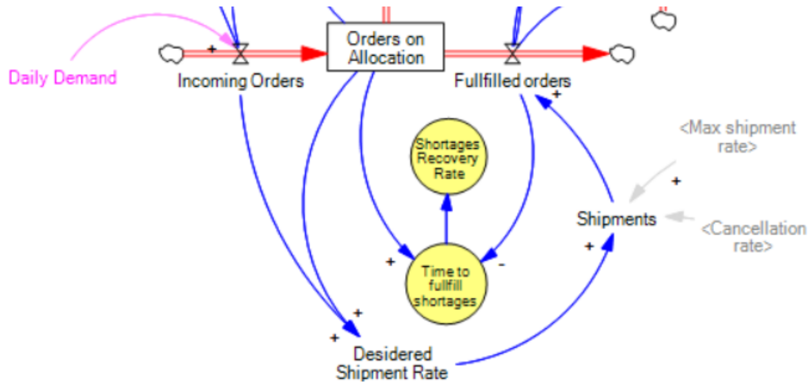


Fig.5.41. *Separation of Actual Delivery Time from Time to Fulfil Shortages*

Time to Fulfil Shortages. The time required by the system to process all the backorders given the current Order Fulfilment Rate.

```
Context = Endogenous          Type = Auxiliary      UOM = days

Time to Fulfil Shortages =
 IF THEN ELSE
  (
```

```
   Fulfilled orders < Orders on Allocation,
   XIDZ(Orders on Allocation,Fulfilled orders, 1),
   0
  )
```

Thus taking the inverse of it allows the definition of the

Shortage Recovery Rate. The daily fraction of processed backorders.

```
Context = Endogenous          Type = Auxiliary     UOM          =
dimensionless

Shortage Recovery Rate = XIDZ(1, Time to Fulfil Shortages, 1)
```

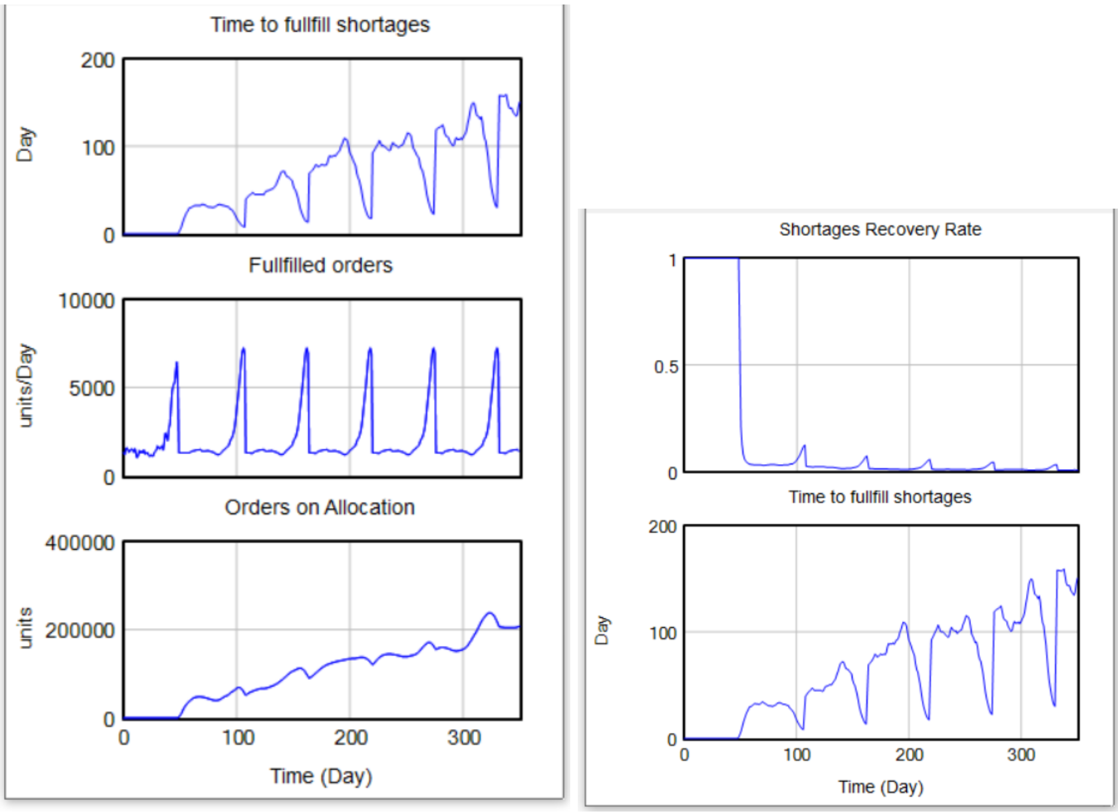


Fig.5.42. *Time to Fulfil Shortage response under extreme testing condition*

5.3.4.3.4. Service Level and Fill Ratio

Investigating on the previous issues led to conclude that service level was evaluated upon a misinterpreted definition. As seen in Chap.1, *Service Level is defined as the probability of not stocking-out during a replenishment cycle*. Thus:

$$\tau_1(s) = \mathbf{P}(X \leq s)$$

where $\boldsymbol{X}$ represents the *Demand During Lead Time*, and $\boldsymbol{s}$ the *Available Stock at the beginning of the replenishment cycle*. In its original formulation (Par. 5.3.1.5), Service Level was estimated instead as the fulfilled fraction of the Desidered Shipment Rate. As it can be seen, this formulation differs substantially from the above mentioned, resembling more the definition of *Fill Ratio.* Therefore, it was decided to separate the two concepts by adding dedicated sections to compute those KPIs in the Order Fulfilment Module, as shown in Fig. 5.43, 5.44. and 5.46.

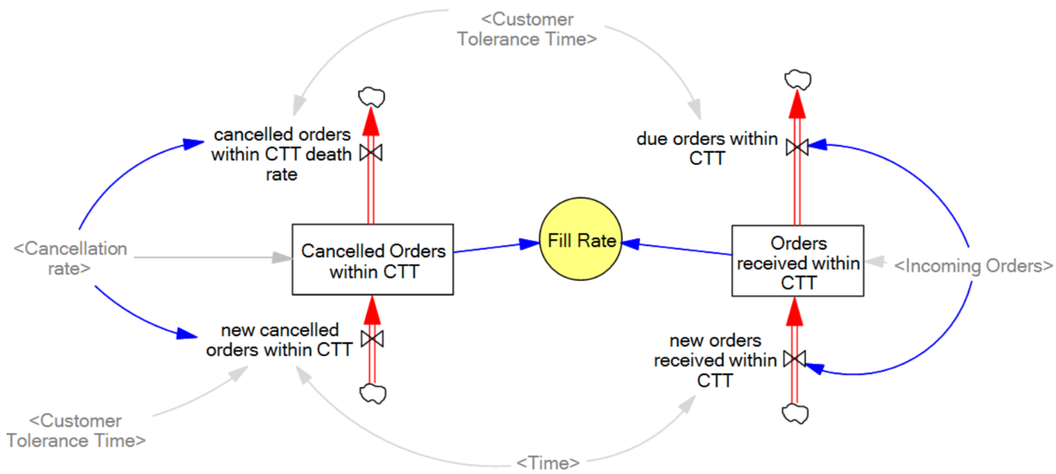


Fig. 5.43. *Definition of Fill Rate in the Order Fulfilment Module*

Fill Ratio. The fraction of customer demand met within the previous CTT period.

```
Context = Endogenous              Type = KPI       UOM =dimensionless

Fill Ratio =   1-XIDZ(Cancelled Orders within CTT, Order received
within CTT previous cycle, 0)
```

The Fill Ratio is conventionally defined as *the fraction of customer demand that is met through immediate stock availability, without backorders or lost sales* and it is typically empirically measured by averaging the number of correctly serviced requests over the total number of requests.

$$\tau_2(s) = \frac{\mathbb{E}[\min(X, s)]}{\mathbb{E}[X]}$$

The formulations for the Cancelled Orders within CTT stock repropose the same logic used for the Orders fulfilled within CTT shown in Par. 5.3.2.2 and therefore they are here omitted.

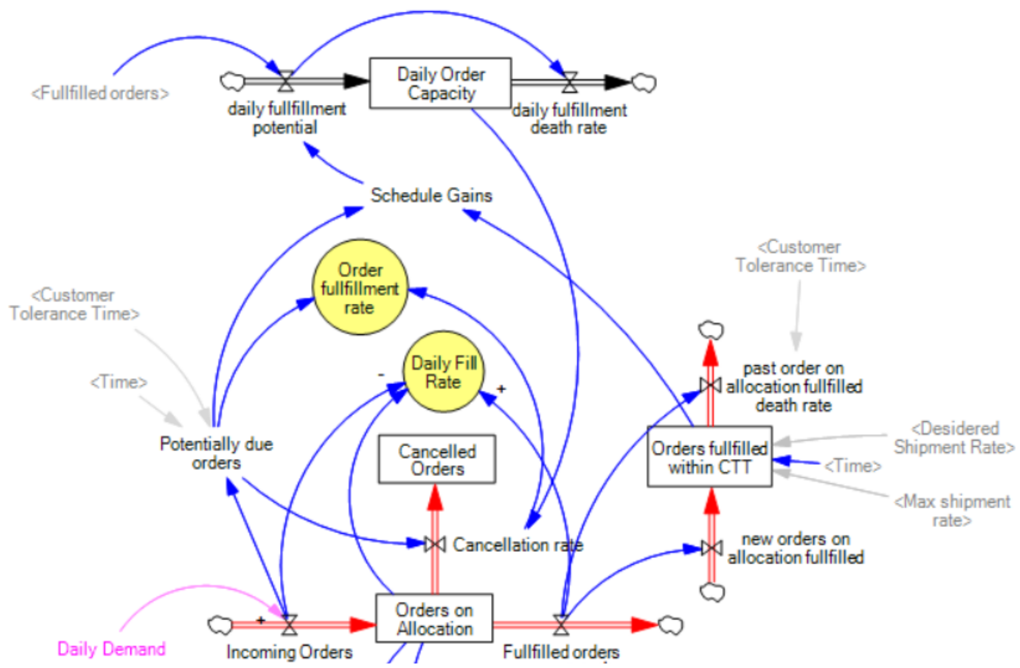


Fig.**5.44.** *Definition of Daily Fill Rate in the Order Fulfilment Module*

Daily Fill Ratio. The system ability to meet new daily demand discarding the efforts in backorders fulfilment.

```
Context = Endogenous              Type = KPI       UOM =dimensionless

Daily Fill Rate =
 IF THEN ELSE
  (
   Fulfilled orders > Orders on Allocation,
   (Fulfilled orders-Orders on Allocation)/Incoming Orders,
   0
  )
```

In other words, in order to also satisfy daily demand in presence of backorders, the system must fulfil orders at a rate greater than its whole backorders stock. Fig. 5.46 shows the response of the newly introduced KPIs to the W-II validation conditions.

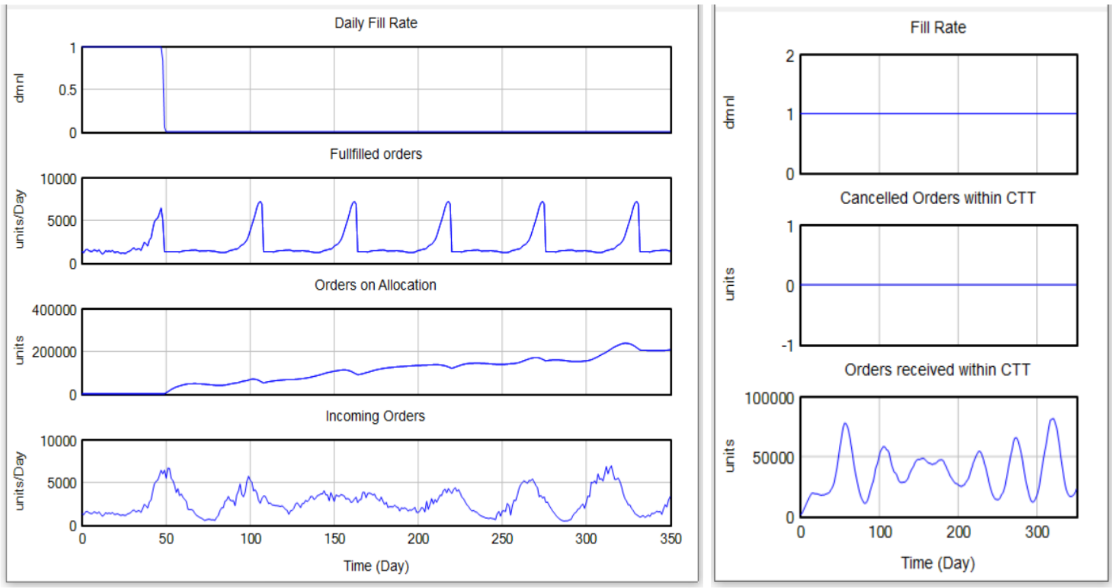


Fig.5.45. *Reformulated Daily Fill Ratio and Fill ratio under extreme condition*

The Service Level is estimated in Fig. 5.46 by adopting a *frequentist probability approach,* hence the total number of times where the Order Received during DLT is lower or equal to Finished Good Inventory at the start of the replenishment cycle are compared with the total number of replenishment cycles occurring within the simulation. At the beginning of each cycle, the Finished Good Inventory available at that moment is delayed up to the end of the cycle where it gets compared with the total accumulated demand received within the cycle. If the first is greater than the latter, the ended cycle counts as a 1 to the total Service Level frequency, increasing the overall Service Level, whereas 0 otherwise. The replenishment lead time is considered equal to the Manufacturing Lead Time because of DDMRP assumption of guaranteed items availability at any moment in any decoupling location.

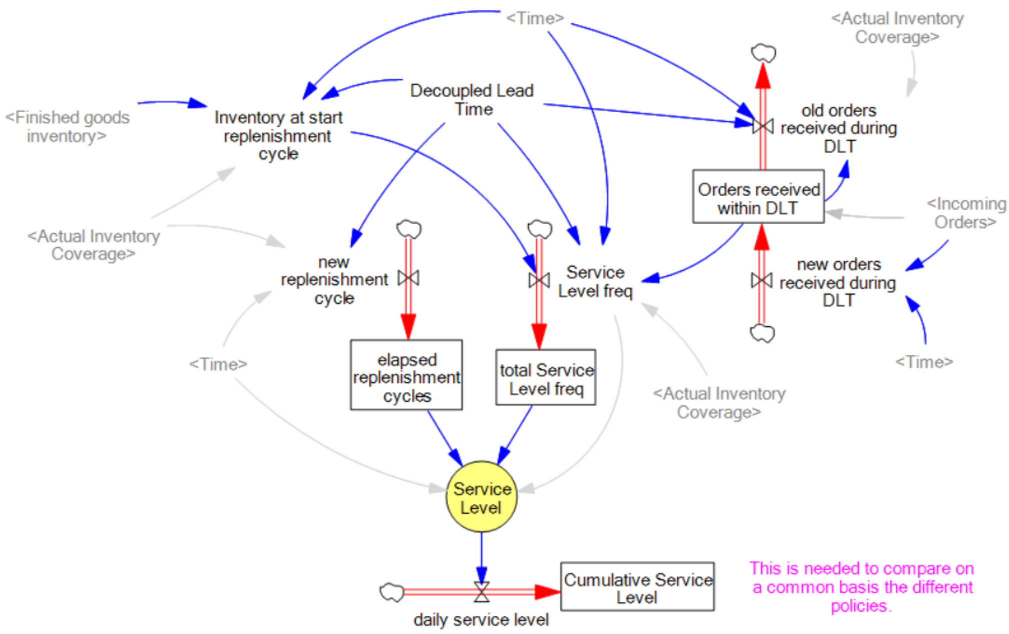


Fig. 5.46. *New implementation of the Service Level*

Reformulated ***Service Level.*** The probability of not stocking-out during a full replenishment cycle.

```
Context = Endogenous            Type = KPI      UOM = dimensionless

Service Level =
 XIDZ
  (
      IF THEN ELSE(Time <>0, Tot Service Level freq, Service Level
freq),
      elapsed replenishment cycles,
      IF THEN ELSE(Time <>0, total Service Level freq, Service Level
freq)
  )
```

Tot Service Level freq. The number of times since the start of the simulation where the Demand during lead time was smaller or equal to the available inventory at the beginning of the replenishment cycle. It represents the numerator of the frequentist probability representing the Service Level.

```
Context = Endogenous            Type = Auxiliary      UOM           =
dimensionless

Tot Service Level freq = INTEGRAL(Service Level freq, 0)
```

Service Level freq. It detects whether the Demand during lead time was smaller or equal to the available inventory at the beginning of the currently ongoing replenishment cycle. It allows detecting when a replenishment cycle counts as TRUE in the frequentist estimation of the Service Level .

```
Context = Endogenous            Type = Auxiliary      UOM           =
dimensionless

Service Level freq =
 IF THEN ELSE
 (
  MODULO(Time,  IF  THEN  ELSE(Time<>0,  Decoupled  Lead  Time,  Actual
Inventory Coverage))=0
:AND:
 Time >0,
  IF   THEN   ELSE(Orders   received   within   DLT<=Inventory   at   start
replenishment cycle,1,0),
 IF THEN ELSE
 (
 (Orders received within DLT*Actual Inventory Coverage)<=Inventory at
start replenishment cycle,
:AND:
Time=0,
1,0
 )
)
```

Elapsed Replenishment Cycle. The number of replenishment cycles has occurred since the start of the simulation. It represents the denominator of the frequentist probability representing the Service Level

```
Context = Endogenous            Type = Auxiliary      UOM           =
dimensionless

Elapsed Replenishment Cycles = INTEGRAL(new replenishment cycle, 0) ;
```

New Replenishment cycle. It detects when a new replenishment cycle is about to start.

```
Context = Endogenous            Type = Auxiliary      UOM           =
dimensionless

New Replenishment cycle =
 IF THEN ELSE
  (
      MODULO(Time,IF  THEN  ELSE(Time<>0,Decoupled  Lead  Time,Actual
Inventory Coverage))=0,
   1, 0
  )
```

Inventory at Start Replenishment Cycle. The value of the Finished Goods Inventory at the beginning of the currently on-going replenishment cycle.

```
Context = Endogenous            Type = Auxiliary      UOM = units

Inventory at Start Replenishment Cycle =
 DELAY MATERIAL
 (
   IF THEN ELSE(MODULO(Time, Decoupled Lead Time)=0, Finished goods
inventory,0),
    IF  THEN  ELSE(Time<>0,  Decoupled  Lead  Time,  Actual  Inventory
Coverage),
  Finished goods inventory,0
 )
```

The formulations for the Orders received within DLT stock repropose the same logic used for the Orders fulfilled within CTT shown in Par. 5.3.2.2 and therefore they are here omitted. Fig. 5.47 presents the new response of the reformulated Service Level to the W-II validation conditions reasonably showing a decrease as the available Finished Good Inventory stocks-out.

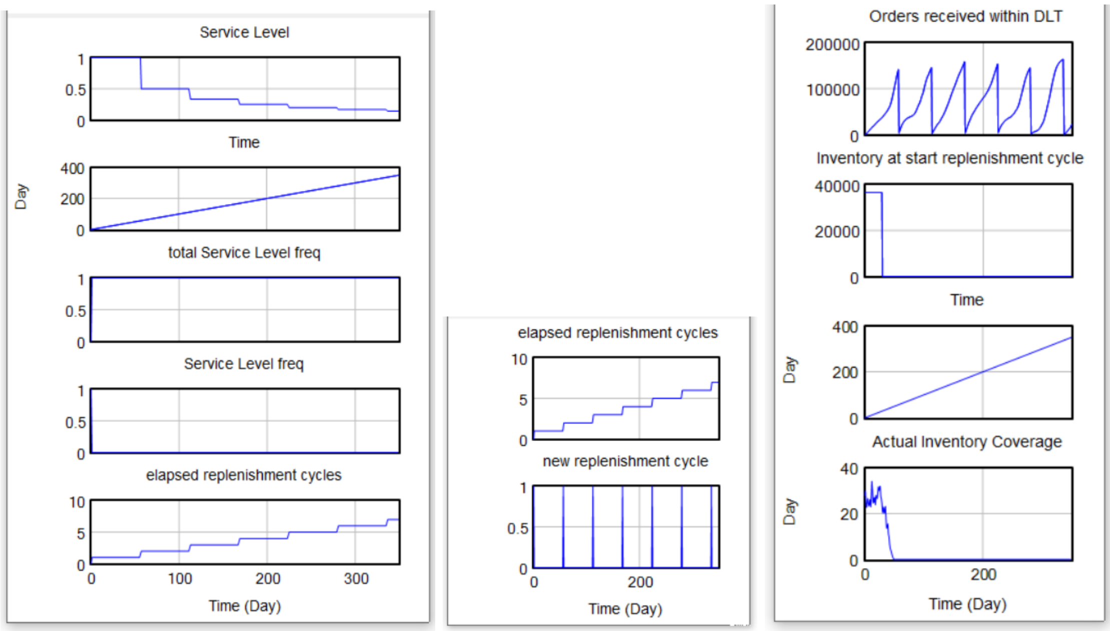


Fig.5.47. *Service Level Response under the initial testing condition after reformulation*

5.3.5. Wave III : Implementing DDMRP

5.3.5.1. Qualified Demand in the Demand Forecasting Module

To port DDMRP logic into the model, the first requirement was being able to compute, or load exogenously, a trend representing the *Daily Qualified Demand*. Unfortunately, no simple implementation was found to allow the determination of qualified demand starting from the Daily Demand input, thus a new variable called *Daily Qualified Demand* was added to the Demand Forecasting Module. To this, multiple trends can be provided exploiting Table functions and the *Demand Scenario* variable which can be used as a switch among all provided demand trends, as shown in Fig. 5.48. This mechanism will be exploited to concurrently benchmark all the multiple datasets needed for validation. Moreover, the qualified demand visibility features can be turned on and off by the Spike Horizon Visibility variable. Turning it off means that the Qualified Demand equals the Daily Demand, thus practically discarding the Spike Alerting logic typical of DDMRP. The addition of this feature was inspired by the work of C.J. Lee where it is implicitly questioned whether the DDMRP claimed benefits are only caused by its Spike alerting logic.

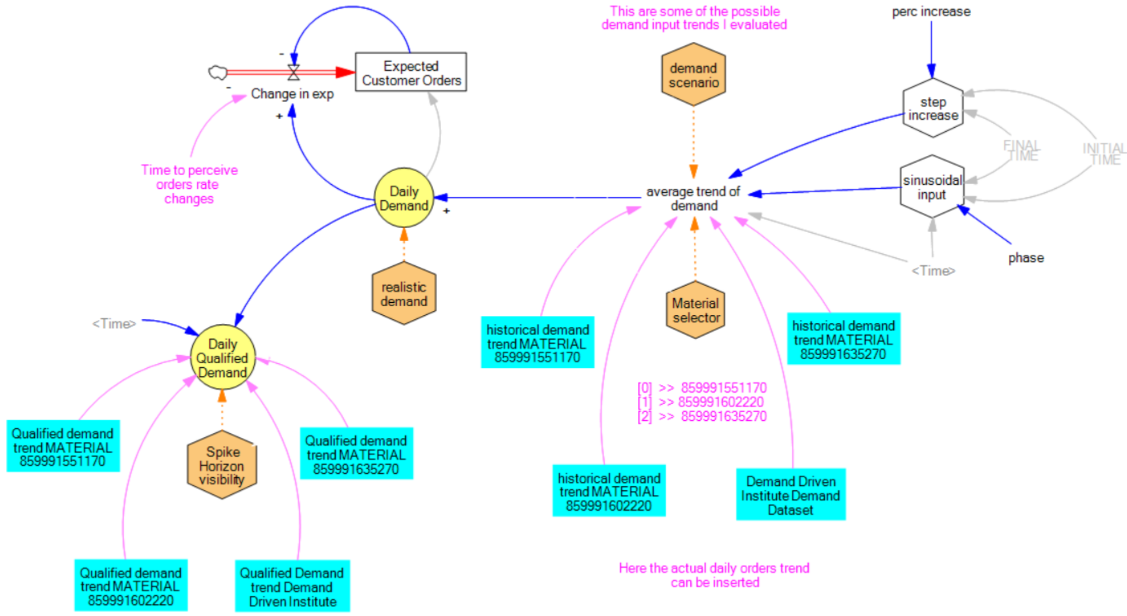


Fig.5.48. *Stock and Flow diagram of the DDMRP customised Demand Forecasting Module*

Spike Horizon Visibility. It allows to deactivate the DDMRP feature of using the Order Spike Rule to compute qualified demand. Removing DDMRP spike visibility is equivalent to running the base model solely on the Daily Demand Input.

```
Context = Endogenous          Type = Scenario       UOM         =
dimensionless
```

Daily Qualified Demand. The Qualified Demand Trend as defined by DDMRP as defined in Chap.2. Given that no mechanism to derive the qualified demand trend was found directly in SD, the trend must be computed externally and loaded by the user using a table function.

```
Context = Exogenous           Type = Lookup         UOM = units/day

IF THEN ELSE(Spike Horizon visibility=1 :AND: demand scenario=2,
  Qualified Demand Trend(Time),
   Daily Demand
  )
```

5.3.5.2. The S&OP module

As seen at the beginning, the basic logic behind the dynamics of the inventory modules is the one of the *stock management problem*. For this reason, it is clear that their behaviour is mostly driven by the dynamical adjustment process of their targeted stock levels.

As initially stated, the modeller's desired DDMRP implementation approach would try to modify as little as possible the base model. Thus, operating on the formulations of the target stock levels seemed the most practical place where to start.

The S&OP module serves this purpose, grouping together all logic necessary to either produce the base model output or the DDMRP one. Separating those logics from the Finished Good Inventory module seemed the best way so as to prevent cluttering the other modules. Fig. 5.49 presentes the structure of the S&OP module. The first thing that jumps to the eye is the absence of stock variables, resembling more a CLD. This is rather unsurprising given that the target inventory levels setting process is one completely driven by manipulating other variables of the system and the environment, without doing any aggregation (thus stocking of quantities). While this might not always be the case (there exists situations where information flows can be also stocked), it was not the case in the proposed model.

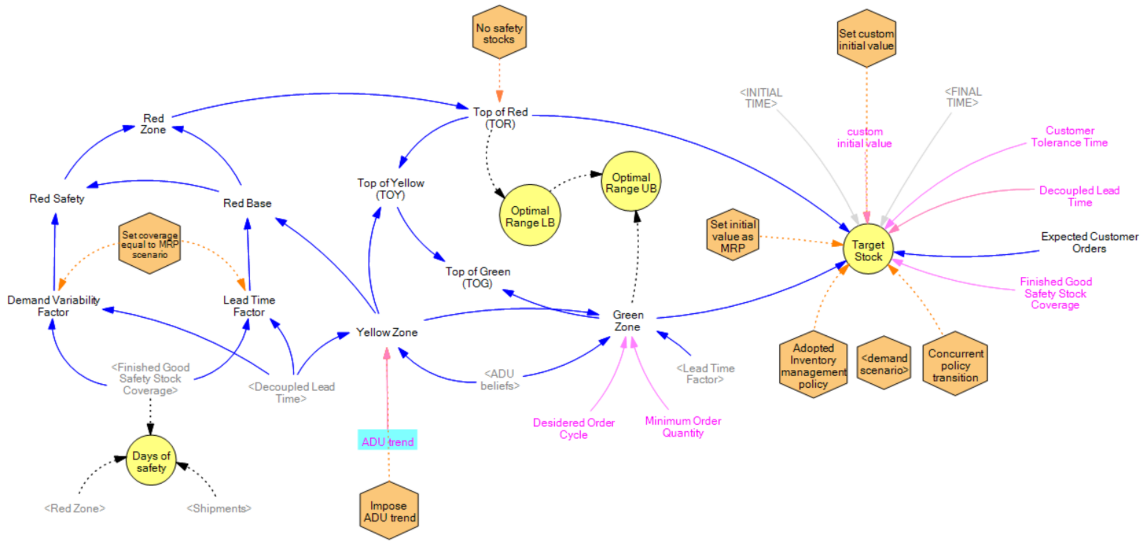


Fig.5.49. *Causal Loop Diagram of the S&OP module to determine the Target Stock in all configurations*

Reformulated ***Target Stock.*** The desired Finished Good Inventory level in either the base model configuration and the DDMRP one.

```
Context = Endogenous              Type = KPI       UOM = units

Target Stock =
((Set initial value as MRP*Expected Customer Orders*(MIN(Customer
Tolerance Time, Decoupled Lead Time)+Finished Good Safety Stock
Coverage))*PULSE(INITIAL TIME,-INITIAL TIME+1))
+
  PULSE(IF THEN ELSE(Set initial value as MRP, 1, INITIAL TIME),FINAL
TIME+1)*
  (
   IF THEN ELSE
   (
    Adopted Inventory management policy=0,
     Expected Customer Orders*(MIN(Customer Tolerance Time, Decoupled
Lead Time)+Finished Good Safety Stock Coverage),
```

```
    IF THEN ELSE
    (
     Concurrent policy transition=0,
     "Top of Red (TOR)"+(0.5*Green Zone),
          (Expected  Customer  Orders*(MIN(Customer  Tolerance  Time,
Decoupled Lead Time)+Finished Good Safety Stock Coverage)*
PULSE(INITIAL    TIME,    60))+("Top    of    Red    (TOR)"+(0.5*Green
Zone))*PULSE(60, FINAL TIME))
   )
  )
```

The extensive formulation above is due to the fact that both base model setting and DDMRP ones are grouped in the same variable. The initial part of the formulation is used to override the initial Target Stock value to a custom one while the original formulation of Target Stock presented in Par. 5.3.1.1 is embedded within multiple IF THEN ELSE statements.

Adopted Inventory Management Policy. It allows the user to select upon which inventory policy to run the model, representing the most impacting scenario variable of the model.

```
Context = Exogenous              Type = Scenario       UOM           =
dimensionless

IF Adopted Inventory Management Policy = 0      THEN        Base
Sterman logic
IF Adopted Inventory Management Policy = 1THEN        DDMRP logic
```

Concurrent Policy Transition. It allows activation of the *Concurrent Policy Transition scenario* where the DDMRP introduction is performed after some time elapsed from simulation start.

```
Context = Exogenous              Type = Scenario       UOM           =
dimensionless
```

Set initial value as MRP. It overrides the initial DDMRP value of the Finished Goods Target Stock so as to let the DDMRP configuration start with the same quantities on hand that would be done under a base configuration.

```
Context = Exogenous              Type = Scenario       UOM           =
dimensionless
```

Green Zone. The Green Zone as defined by DDMRP as defined in Chap. 2

```
Context = Endogenous             Type = Auxiliary      UOM = units

Green Zone =
INTEGER(
```

```
  MAX(
    MAX(
       Yellow Zone*Lead Time Factor,
       Desidered Order Cycle*ADU beliefs),
  Minimum Order Quantity
  )
)
```

ADU beliefs. Being defined by variables pertaining to the Suppliers Module, its formulation is detailed in Par. 5.3.5.4.

Yellow Zone. The Yellow Zone as defined by DDMRP as defined in Chap. 2

```
Context = Endogenous              Type = Auxiliary      UOM = units

Yellow Zone = INTEGER(Decoupled Lead Time*ADU beliefs)
```

Red Zone. The Red Zone as defined by DDMRP as defined in Chap.2

```
Context = Endogenous              Type = Auxiliary      UOM = units

Red Zone = INTEGER(Red Base+Red Safety)
```

Red Safety. The Red Safety as defined by DDMRP in Chap. 2

```
Context = Endogenous              Type = Auxiliary      UOM = units

Red Safety = Red Base*Demand Variability Factor
```

Red Base. The Red Base as defined by DDMRP as defined in Chap. 2.

```
Context = Endogenous              Type = Auxiliary      UOM = units

Red Base = Yellow Zone*Lead Time Factor
```

Demand Variability Factor. The Demand Variability Factor as defined by DDMRP as defined in Chap. 2.

```
Context = Endogenous              Type = Auxiliary      UOM         =
dimensionless

Demand Variability Factor = Set Coverage equal to MRP scenario =
IF    THEN    ELSE(Set    coverage    equal    to    MRP    scenario=0,
0.5,(-1+(1-(4*(-(Finished Good Safety Stock Coverage/Decoupled Lead
Time))))^(1/2))/2)
```

Demand Variability Factor is set by default to 0.5. In its formulation the exact computation to let Demand Variability Factor yield the same inventory coverage under a base model configuration, is performed. The computation assumes that

LFT = DVF
TOR = Finished Good Safety Stock Coverage (see Par. 5.3.1.1)

Lead Time Factor. The Lead Time Factor as defined by DDMRP as defined in Chap.2.

```
Context = Endogenous            Type = Auxiliary      UOM          =
dimensionless

Lead Time Factor  =
IF   THEN   ELSE(Set   coverage   equal   to   MRP   scenario=0,
0.5,(-1+(1-(4*(-(Finished  Good  Safety  Stock  Coverage/Decoupled  Lead
Time))))^(1/2))/2)
```

Lead Time Factor is set by default to 0.5. In its formulation the exact computation to let Lead Time Factor yield the same inventory coverage under a base model configuration, is performed. The computation assumes that

LFT = DVF
TOR = Finished Good Safety Stock Coverage (see Par. 5.3.1.1)

Set Coverage equal to MRP scenario. It allows activation of the *"Same as MRP coverage" scenario* for the DDMRP configuration where there Finished Goods Inventory is managed by DDMRP so as to obtain the same inventory coverage pursued with the base configuration. Hence, this variable triggers the alternative formulation for Lead Time Factors and Demand Variability Factors mentioned above.

```
Context = Exogenous             Type = Scenario       UOM = units
```

Days of Safety in the Buffer. The Days of Safety within the buffer as defined by DDMRP in Chap. 2.

```
Context = Endogenous            Type = Auxiliary      UOM = days

Days of Safety = XIDZ(Red Zone, Shipments, Finished Good Safety Stock
Coverage)
```

Desired Order Cycle. The desired number of days planners would like to release replenishment orders in a DDMRP configuration. (see Chap. 2)

```
Context = Exogenous             Type = Auxiliary      UOM = days
```

Minimum Order Quantity. The SKU specific Minimum Order Quantity negotiated by procurement through Purchasing Agreements.

```
Context = Exogenous                Type = Auxiliary      UOM = units
```

Top-of-Red (TOR). The Top-of-Red as defined by DDMRP in Chap. 2.

```
Context = Endogenous               Type = Auxiliary      UOM = units

Top-of-Red (TOR) = Red Zone*(1-No safety stocks)
```

No DDMRP Safety Stocks. It allows activation of the *"No DDMRP Safety Stock" scenario* where the DDMRP Top-of-Red value is overridden to 0. This was required to account for some Whirlpool DDMRP managed SKUs where no TOR was set.

```
Context = Exogenous                Type = Scenario       UOM              =
dimensionless
```

Top-of-Yellow (TOY). The Top-of-Yellow as defined by DDMRP. as defined in Chap.2.

```
Context = Endogenous               Type = Auxiliary      UOM = units

Top-of-Yellow (TOY) = "Top of Red (TOR)"+Yellow Zone
```

Top-of-Green (TOG). The Top-of-Green as defined by DDMRP in Chap. 2.

```
Context = Endogenous               Type = Auxiliary      UOM = units

Top-of-Green (TOG) = "Top of Yellow (TOY)"+Green Zone
```

Optimal Range UpperBound. The Optimal Inventory Upperbound as defined by DDMRP in Chap. 2.

```
Context = Endogenous               Type = Auxiliary      UOM = units

Optimal Range UpperBound = Optimal Range LB+Green Zone
```

Optimal Range LowerBoud. The Optimal Inventory Lowerbound as defined by DDMRP in Chap.2.

```
Context = Endogenous               Type = Auxiliary      UOM = units

Optimal Range LowerBoud = "Top of Red (TOR)"
```

5.3.5.3. Customisation to the Finished Good Inventory module

5.3.5.3.1. Net Flow Position

The second important requirement to port DDMRP into the model was computing the *Net Flow Position* used to generate replenishment orders through the Net Flow Equation. Fig. 5.50 introduces the customisation required to bring the change in the Finished Good Inventory Module. To improve model clarity, here a parallel was drawn with the base model, given that the Net Flow equation basically overrides the base model replenishment rule (see paragraph ##). The Desired Daily Production variable formulation was thus required to change depending on the selected inventory policy. To do this, the *Adopted Inventory Management Policy* variable was added to act as a toggle in all variables whose formulation would change depending on the policy set (e.g. Desirable Daily Production), as shown in Fig. ##.

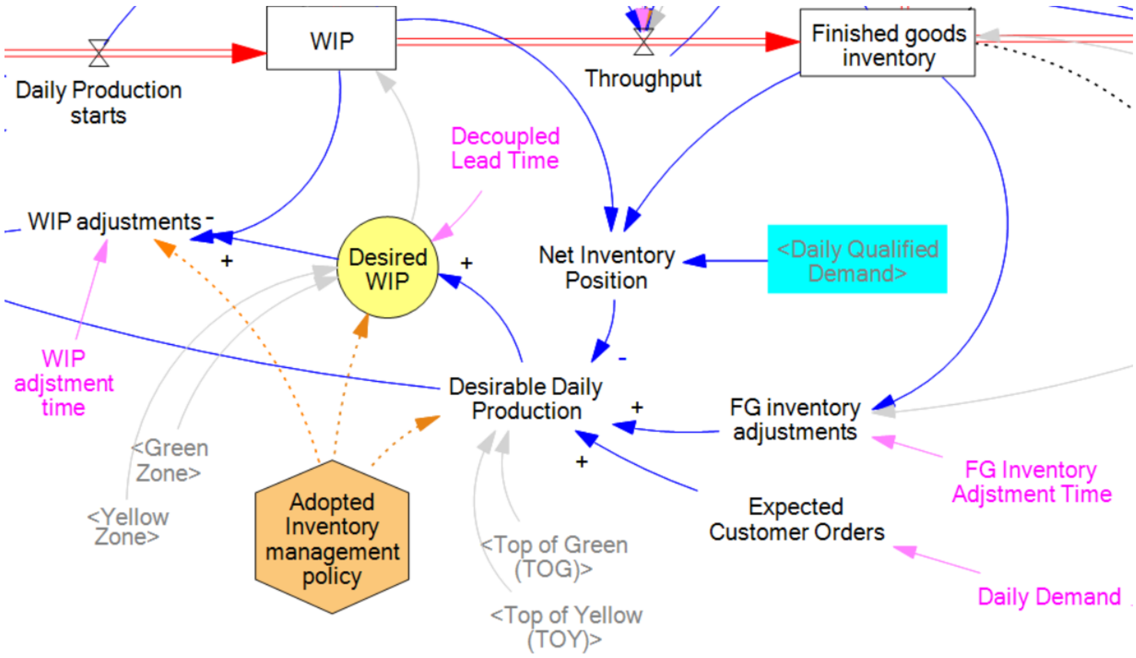


Fig.5.50. *Introduction of the Net Inventory Position variable in the Finished Good Inventory Module*

> ***Net Inventory Position.*** The Net Flow Position as defined by DDMRP. as defined in Chap. 2.
>
> `Context = Endogenous          Type = Auxiliary      UOM = units`
>
> `Net Inventory Position = (Finished goods inventory+WIP-Daily Qualified Demand)`

An interesting point emerged regarding the WIP adjustments, used in Sterman to let managers take into account the state of the supply line in their re-ordering rule. To run the DDMRP configuration, the WIP adjustments variable is required to be inactive, being the reordering rule completely handled by the Net Flow Equation, thus suggesting that DDMRP actually does not consider the status of the Supply Line in its reorder rule. However, this is an incorrect conclusion given that the Net Flow Equation rule is using the Net Inventory Position to seize replenishment orders, thus fully considering the status of the Supply Line (see Chapter. 1). Being in the strong interest of the modeller to modify the base model as less as possible, it was tried to not deactivate the WIP adjustments logic, letting the Net Flow Equation only compare On-hands quantities with qualified demand and then determining the size of the adjustments for the supply line as the deviation of the WIP from the TOY. However, this approach produced a less stable behaviour of the DDMRP thus it was discarded.

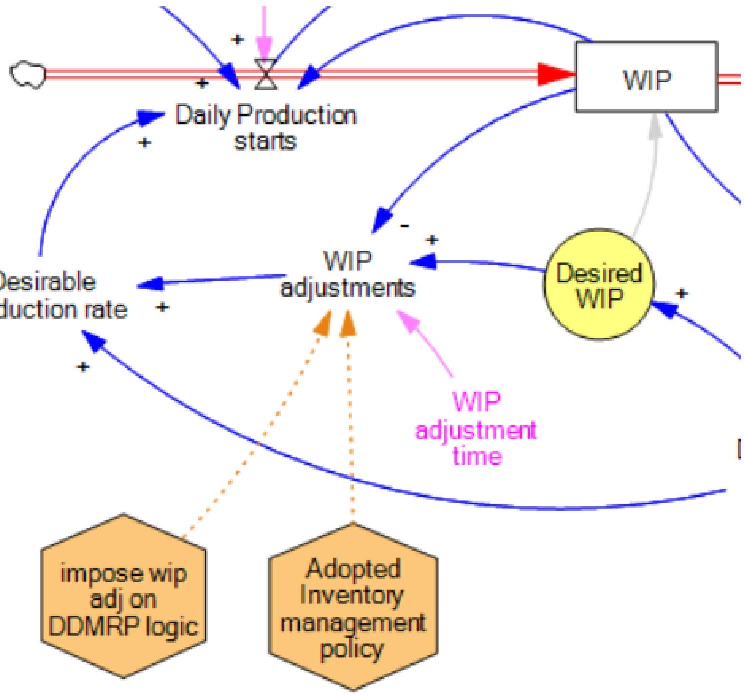


Fig.5.51. *Deactivation of Finished Goods Inventory Supply Line Adjustments in DDMRP configuration*

5.3.5.3.2. Excess and Shortages

With all the logic to compute the DDMRP Buffer thresholds in place in the S&OP module, a primal implementation to evaluate Excesses and Shortages was finally added to the Finished Goods Inventory Module.

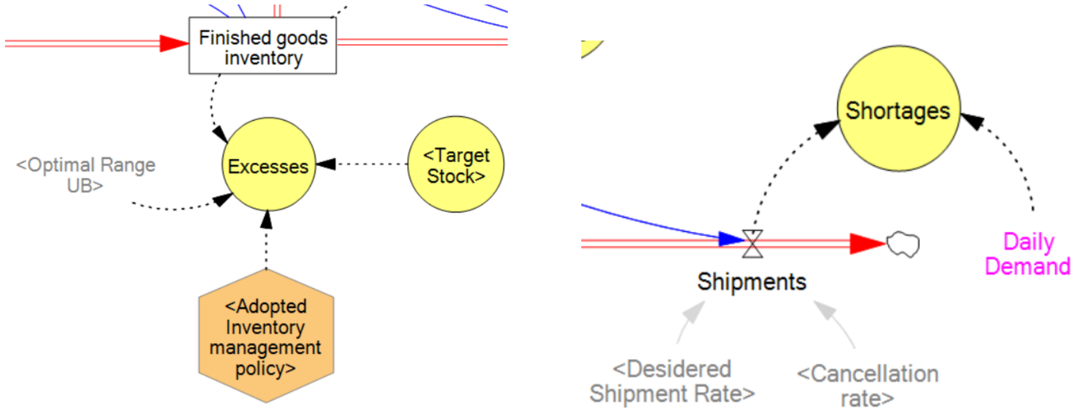


Fig.5.52. *Excess and Shortage primal implementation in the model*

Excesses. The quantity overshooting the targeted inventory levels. Because DDMRP implies an oscillatory equilibrium, as shown in Par. 5.3.5.6, the DDMRP configuration excesses are considered only after the Finished Good Inventory overshoots the Optimal Inventory Range Upperbound.

```
Context = Endogenous              Type = Auxiliary      UOM = units

Excesses =
IF THEN ELSE
(
 Adopted Inventory management policy=0,
 MAX(Finished goods inventory-Target Stock,0),
 MAX(Finished goods inventory-Optimal Range UB,0)
)
```

Shortages. All daily demanded quantities that were not shipped on the same day. It represents the Fill ratio in terms of material units rather than a ratio.

```
Context = Endogenous              Type = Auxiliary      UOM = units

Shortages = MAX(Daily Demand-Shipments, 0)
```

5.3.5.4. The ADU estimation module

Fig. 5.53 introduces the ADU estimation module. As seen in Chapter 1, the *Average Daily Usage* is at the heart of DDMRP buffer dimensioning, being thus the most important metric in DDMRP. In its textbook DDI proposes various methods to compute ADU, Whirlpool adopted a blended estimation of it based on a 12-week ABCXYZ dynamic window, as introduced in Chapter 2. Hence, the same logic is implemented in the proposed model, with some exceptions, by reutilizing the expectation creation mechanism used in Sterman for the Demand Forecasting Module. That is, the ADU trend is treated as if it was a forecast on future consumption that gets updated everyday.

The trend is created by a 6-week moving average of past consumption blended with a 6-week estimation of future consumptions. The window size can be changed depending on the ABC-XYZ classification of the SKU analysed.

Being unknown to the modeller how to introduce the concept of "future values" in System Dynamics (while it is pretty easy instead to delay quantities in the future), the future expectations about ADU are given by the latest value of the expected orders beliefs, thus it is assumed that future consumptions stay fixed to what the manager currently believe would be during all the considered future weeks. However, this assumption plays a determinant limitation to the model capability to properly represent DDMRP logic. On the other hand, to have a fair comparison between different policies it should always be considered what is the real information available to the managers of the system: if information about future trends would be known to the DDMRP manager, they should be known and used also by the non-DDMRP one. Thus, given that the non-DDMRP manager does not use this information, this approach makes comparisons fairer.

To compute the moving average instead the values of the Desired Shipment Rate has been used. Values are accumulated in a stock, building the numerator of the moving average to then be divided by the days included in the past ADU window, so as to extract the average. The average moves because the stock is constantly increased by the new values of Desired Shipment RAte and decreased by a MATERIAL DELAY over the same input values lasting exactly the same number of days in the ADU review window. While at first glance using the Desired Shipment Rate for estimating ADU, rather than daily Shipments, seems a trivial mistake, it must be considered that when the system cannot fulfil orders due to a stock-out, shipments go and stay to zero while the Desired Shipment Rate jumps. If the Shipments were to be used instead of the Desired Shipment Rate, then extended periods of stockouts would produce a *reduction in buffer sizes rather than an increase* as it should be to recover from shortages. A debatable point is instead possible on the use of the Expected Customer Orders to estimate ADU. This approach has been discarded because Expected Customer Orders only account for the daily portion of demand, without considering the accumulated backorders.

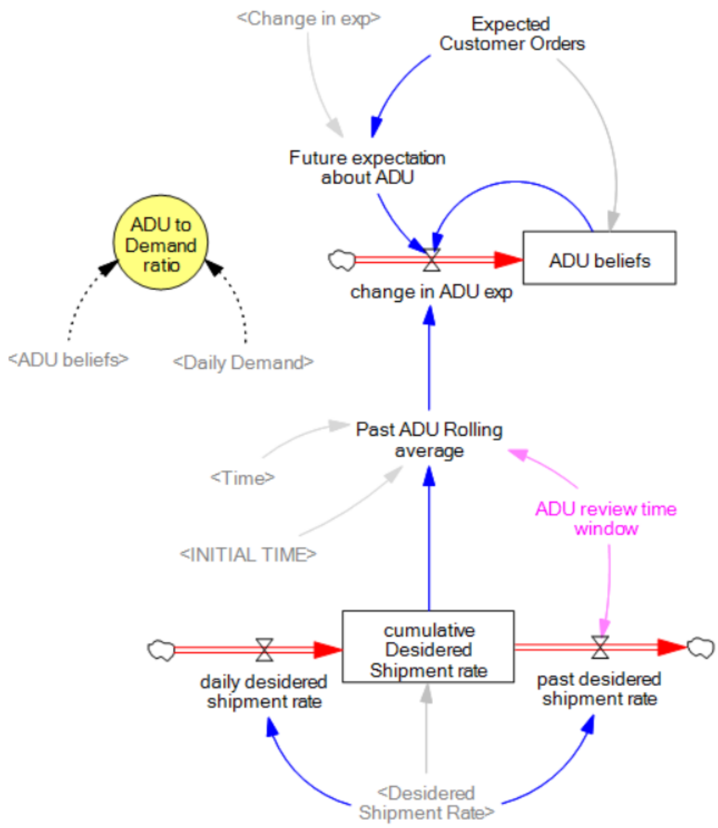


Fig.5.53. *Stock and Flow diagram of the ADU estimation module*

ADU beliefs. The manager smoothed expectations about ADU.

`Context = Endogenous          Type = Stock          UOM = units/day`

`ADU beliefs = INTEGRAL(change in ADU exp, Expected Customer Orders)`

Change in ADU Expectations. The forecasting error affecting manager's beliefs about ADU. ADU is evaluated by means of a blended approach, averaging past and future desired consumptions.

`Context = Endogenous          Type = Auxiliary          UOM = units`

`Change in ADU Expectations = INTEGER(((Past ADU Rolling average+Future expectation about ADU)/2)-ADU beliefs)`

Past ADU Rolling Average. The past ADU moving average used to blend manager past ADU expectations with future ones.

`Context = Endogenous          Type = Auxiliary          UOM = units/day`

```
Past ADU Rolling Average = cumulative Desidered Shipment rate/IF THEN
ELSE (Time<ADU review time window, Time+1,ADU review time window)
```

Cumulative Desired Shipment Rate. The accumulation of all Desired Shipment Rates occurred during the ADU review time window. It creates the numerator of the past ADU moving average.

```
Context = Endogenous            Type = Stock          UOM = units

Daily  Desired  Shipment  Rate  =  INTEGRAL(daily  desidered  shipment
rate-past desidered shipment rate, Desidered Shipment Rate)
```

Past Desired Shipment Rate. The values of Desired Shipment Rate that must be subtracted at each iteration from the Cumulative Desired Shipment Rate.

```
Context = Endogenous            Type = Flow           UOM = units/day

Past Desired Shipment Rate = DELAY MATERIAL(Desidered Shipment Rate,
ADU review time window-1, 0, 0)
```

ADU review time window. The size of the past ADU moving average window.

```
Context = Exogenous             Type = Auxiliary      UOM = days
```

5.3.5.5. The Financial Performances module

Fig. 5.54 introduces the Stock and Flow diagram used to extract financial performances from the model response. As said, since the beginning of the modelling phase all financial metrics were put temporarily aside, thus the following subsection is still considered a Work-in-Process. On the other hand, as stated in Simchi-Levi, cost minimisation plays the pivotal role in all supply chain problems. Hence, the final aim of the modeller was to compress all model performances down to the single metric of *SKU Direct Contribution Margin* (DCM), being this metric the one that typically drove GSS analysts and leaders' decision making. Unfortunately, as expected it was impossible to determine with certainty the underlying key variables that yield to the DCM, thus it does not appear in the current formulation. It was possible instead to start evaluating typical financial metrics used in to benchmark the inventory performances, including the Whirlpool-own definition of obsolescence risk (see Chapter 2).

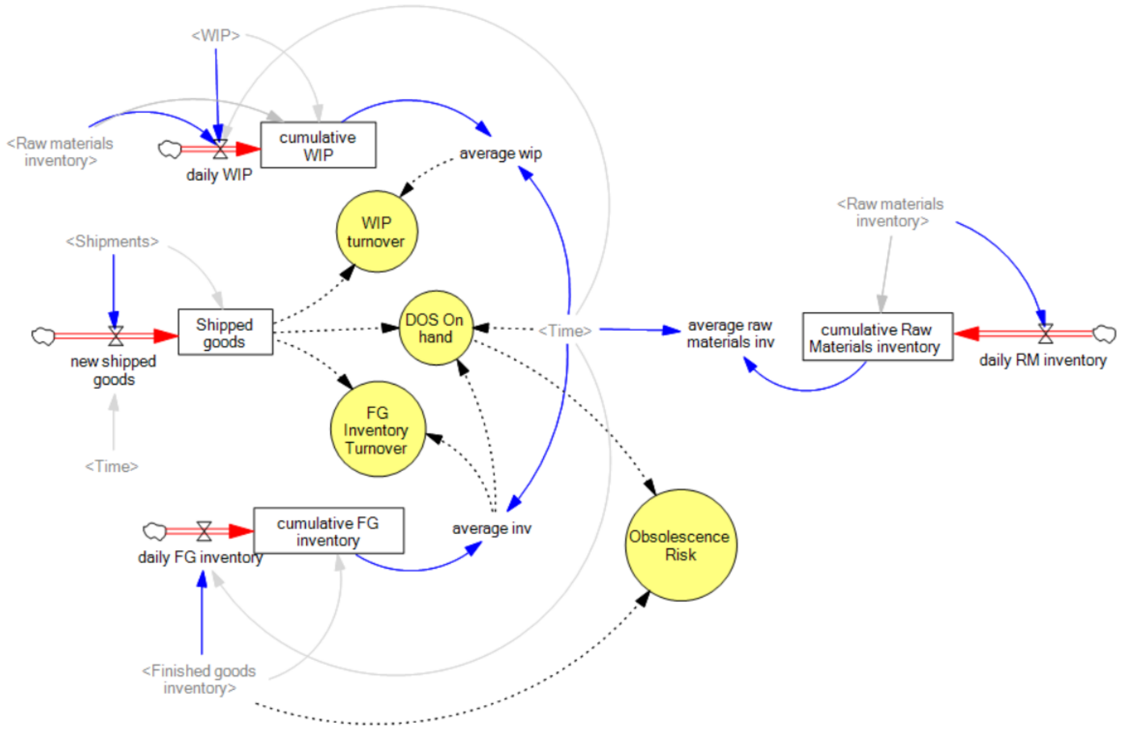


Fig.5.54. *Stock and Flow diagram of the Financial Performances module*

FG Inventory Turnover. It measures the speed with which Finished Goods Inventory gets replaced. As seen in Chap.1, it is a strongly used metric to evaluate company efficiency in exploiting inventory as an asset.

```
Context = Endogenous                Type = KPI       UOM = days

FG Inventory Turnover = XIDZ(Shipped goods,average inv, 0)
```

WIP Turnover. It measures the speed with which WIP Inventory gets replaced. It can be used to assess whether there exists excess capacity or monitor production related issues.

```
Context = Endogenous                Type = KPI       UOM = days

WIP Turnover = XIDZ(Shipped goods,average wip, 1)
```

DOS on hand. Also known as the *Days of Inventory On-Hand (DOH)* it is used to measure how much of the company's liquidity is tied up in inventory.

```
Context = Endogenous                Type = KPI       UOM = days

DOS on hand = XIDZ(average inv*MAX(Time, 1), Shipped goods, 0)
```

Obsolescence Risk. The economic value at risk associated with potential obsolescence of Finished Goods currently kept.

```
Context = Endogenous              Type =KPI       UOM = EUR

Obsolescence Risk = (DOS On hand/365)*Finished goods inventory
```

The DOS On-Hand are used as an estimate of average life of the Finished Goods stocked in current inventory so as to evaluate their obsolescence risk as defined by Whirlpool (see Chap.3). The monetary value of obsolescence is considered directly proportional to its volumes, thus Obsolescence Risk like "1 EUR" in reality means that 1 Finished Good is risking obsolescence and that might count as the full monetary value of the item (e.g. 850 EUR).

Shipped Goods. The accumulation of all shipments throughout the simulation.

```
Context = Endogenous              Type =KPI       UOM = units

Shipped Goods = INTEGRAL(Shipments, Shipments)
```

Cumulative FG Inventory. The accumulation of all levels of the Finished Goods Inventory throughout the simulation.

```
Context = Endogenous              Type =Stock           UOM = units

Finished Goods Inventory= INTEGRAL(Finished Goods Inventory, Finished
Goods Inventory)
```

Average FG Inventory. The average Finished Goods Inventory kept during the simulation.

```
Context = Endogenous              Type = KPI      UOM = units/day

Average FG Inventory = cumulative FG inventory/MAX(1, Time)
```

Cumulative WIP Inventory. The accumulation of all levels of the WIP throughout the simulation.

```
Context = Endogenous              Type =Stock           UOM = units

Cumulative WIP Inventory = INTEGRAL(WIP, WIP)
```

Average WIP Inventory. The average WIP Inventory kept during the simulation.

```
Context = Endogenous            Type =KPI       UOM = units/dat

Average WIP Inventory = cumulative WIP inventory/MAX(1, Time)
```

Cumulative Raw Materials Inventory. The accumulation of all levels of the Raw Materials Inventory throughout the simulation.

```
Context = Endogenous            Type =Stock           UOM = units

Cumulative Raw Materials Inventory = INTEGRAL(Raw Materials
Inventory, Raw Materials Inventory)
```

Average Raw Materials Inventory. The average Raw Materials Inventory kept during the simulation.

```
Context = Endogenous            Type =KPI       UOM = units/day

Average Raw Materials Inventory = cumulative Raw Materials
Inventory/MAX(1, Time)
```

5.3.5.6. DDMRP oscillatory equilibrium condition

Before diving into the full validation phase of W-II, it was in the interests of the modeller to assure that the equilibrium properties of all modules were preserved after the substantial changes brought by the DDMRP additions.

It turns out that the DDMRP replenishment rule imposes an *oscillatory equilibrium* of inventory on-hand around the target inventory value (see Chap.2), as shown in Fig. 5.55. This seems due to the fact that, differently from the Sterman base case, a replenishment order is issued upon a rather *non-continuous rule*, issuing orders only when the Net Inventory Position falls below the Top-of-Yellow for a quantity that is bounded to be at least equal to the Green Zone (Fig. 5.56). This logic obliges the inventory on-hand to gradually lower until a new order is released and new quantities are resupplied. It is worth noticing that this chainsaw trend is also what is typically considered when introducing continuously reviewed (s, S) inventory policies in Simchi-Levi, Chap.2. The system was hence considered in equilibrium when this pattern emerged and the order release function presented a “as uniform as possible” trend (e.g. always releasing roughly the same quantities after a certain number of days).

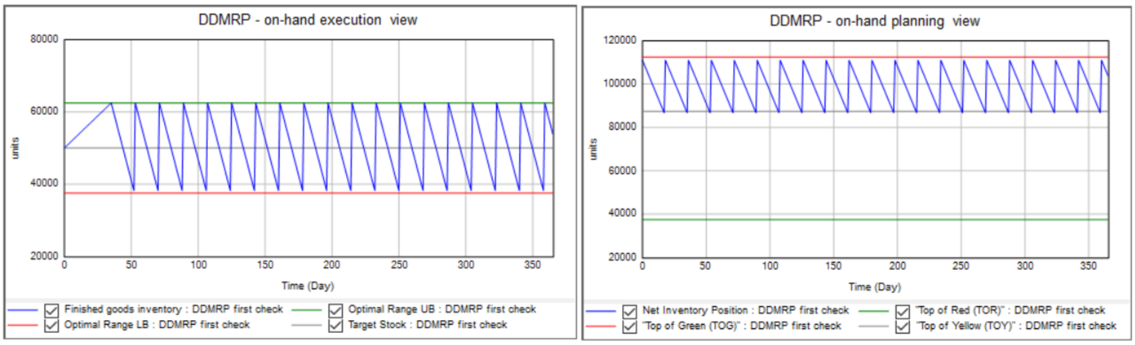


Fig.5.55. *DDMRP oscillatory equilibrium condition under a constant demand input*

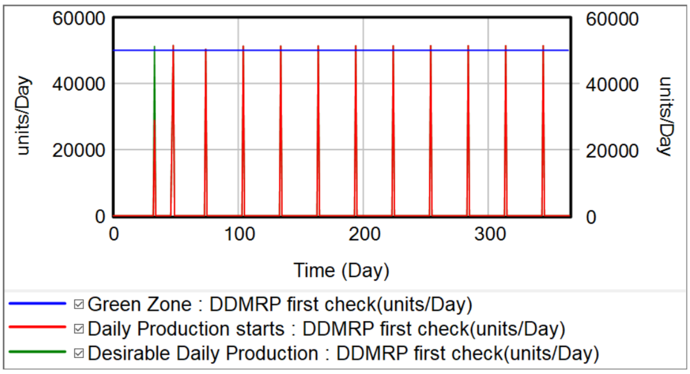


Fig.5.56. *Discrete DDMRP order release rule under equilibrium conditions*

As can be seen by its formulation provided in paragraph ##, an important remark emerged while setting initial conditions for the *Desired WIP*. At a first glance, by reviewing DDMRP theory, it would seem straightforward that *the yellow zone is the desired WIP in DDMRP configuration, being the yellow zone equal to the cycle inventory*. On the other hand, if this configuration gets loaded in the model, the system does not present the expected oscillatory equilibrium condition in Fig. 5.55. Thus, an exact formulation for the initial WIP that would have ensured initial equilibrium was sought. To be in equilibrium, regardless of any adopted policy, the quantities withdrawn from a stock must equal the one entering in it. Hence, the following formulation for Desired WIP follows :

```
Initial Finished Goods Inventory = Target Inventory = OH(0)
Initial Top-of-Red = TOR(0)
Initial Green Zone = GZ(0)
Initial Net Flow Position = NFP(0)
Initial WIP = Desired WIP = WIP(0)
Initial Daily Demand = DD(0) = exogenous
Initial Throughput = THR(0)
Initial Daily Production Starts = DPS(0)
Initial Daily Shipments = SHIP(0)

OH(0)   = TOR(0) + ( 0.5*GZ(0) ) ;
SHIP(0) = DD(0) ;
NFP(0)  = OH(0) + WIP(0) - DD(0) ;
```

```
THR(0)  = MATERIAL DELAY(DPS(0)) ;
To keep the WIP stock equilibrium :
 THR(0) = DPS(0) ;

To keep Finished Goods stock equilibrium :
 THR(0) = SHIP(0) ;
```

Thus :

```
DPS(0)  = f(NFP(0)) = TOG(0) - NFP(0) = SHIP(0) = DD(0) ;
SHIP(0) = TOG(0) - OH(0) - WIP(0) + DD(0) = DD(0) ;

WIP(0) = TOG(0) - TOR(0) - 0.5*GZ(0)
       = (TOR(0) + YZ(0) + GZ(0)) - TOR(0) - 0.5*GZ(0)
       = YZ(0) - 0.5*GZ(0) < YZ(0) ;
```

Loading the above condition for Desired WIP indeed produced the equilibrium conditions shown in Fig. 5.55. This result confirm the initial belief of

Desired WIP = Yellow Zone

but it also shows that the half of minimum order size (see Chapter 2) must be subtracted to the yellow zone to take full account of the status of the WIP supply line and so let the DDMRP system start in equilibrium.

Struggling in finding a proper initial system equilibrium conditions for DDMRP environments is something that also showed up during the 2014 APICS Conference, when E. Bush, CEO of Demand Driven Technologies, embarked into a "live simulation of DDMRP" by constructing a random demand function grouping answers from the audience. The approach used in that occasion is the one typically adopted also by other authors of "*establish a period of prior history to enable the buffer to settle into an expected behaviour*" (E. Bush). Through the above equilibrium formulation this condition is unnecessary in the proposed model.

Finally, Fig. 5.57 shows that DDMRP logics work properly in face of step increase in demand, updating the ADU beliefs proportionally to the increase. The shift in the buffer thresholds is also followed by the Net Flow Equation logic, never letting the Net Inventory Position to fall below Top-of-Yellow. The value of the Finished Good Inventory oscillates around the new Target Inventory value following the step increase. These initial encouraging results allowed the modeller to move toward a detailed validation phase of W3.

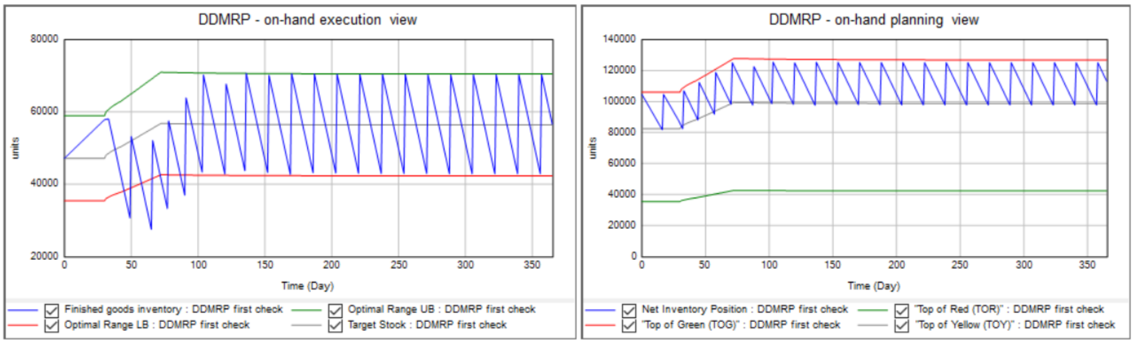


Fig.5.57. *DDMRP Oscillatory equilibrium with a 20% step increased demand input*

5.3.6. Wave III validation: Model response to the Demand Driven Institute dataset

5.3.6.1. Testing Conditions

For the purpose of validating W-III, an extensively validated DDMRP dataset was desirable for testing whether the customisations introduced to port the DDMRP logic in the model worked correctly. Such a dataset should not be extremely difficult to analyse in order to facilitate the issue-detection phase, given that the major additions done during W-III could already turn into multiple sources of noise. Finally, a huge advantage would be *if the selected dataset were also known to Whirlpool employees involved in the DDMRP transition project* (see Chap. 3), so that no "learning barriers" would interfere during the model sharing phase, *easing the acceptance of the model and its review*.

As introduced in Chapter 2, the *Demand Driven Institute* (DDI) is the global reference institution regarding DDMRP, having developed the methodology in 2011 and nowadays providing extensive ASCM-certified company training programs about it (e.g. Demand Driven Planner (DDP), Demand Driven S&OP Leader (DDL) Programs). In 2013 DDI released the third edition of its original DDMRP textbook, representing the DDMRP most updated body-of-knowledge. In Chapter 9 (pp. 209-226) of the textbook a learning-oriented "step-by-step" 21-days simulation of the DDMRP behaviour is provided for a finished product having the following buffer profile.

Example Part Buffer For Simulation			
Average Daily Usage	10	Green Zone	**35**
Buffer Profile	M, M (.5), M (.5)		LT Factor: 35 (DLT (7)x ADU (10) x Lead Time Factor (.5))
MOQ	20		Minimum Order Quantity: 20
Imposed or Desired Order Cycle (DOC)	None		Order Cycle: N/A
Decoupled Lead Time (DLT)	7 days	Yellow Zone	**70** (7(DLT) x 10(ADU))
Order spike threshold = 26 **Order Spike Horizon = 8 days**		Red Zone	**52** (Red Base (35) + Red Safety (17))
			Red Base: 35 (DLT (7)x ADU (10) x Lead Time Factor (.5))
			Red Safety: 17 (Red Base (35) x Variability Factor (.5))

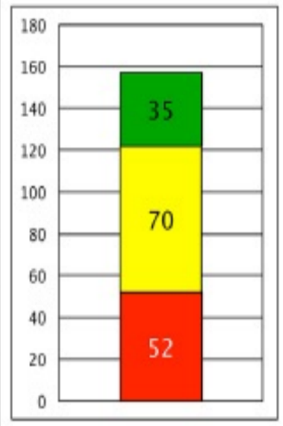


Fig.5.58. *The DDI simulation buffer profile for the example component*

The DDI example featured all the desidered requirements for initiating the validation of W-III. Moreover *- and maybe the most important aspect of it -* GSS management invested in educating their material planners about DDMRP by purchasing the full stack of DDI corporate learning programs. Thus, the following dataset is well-known and "accepted as valid" by them. Fig. 5.59 shows the Qualified Demand and Daily Demand and trends used in the DDI simulation. Those were provided to the model by means of Lookups.

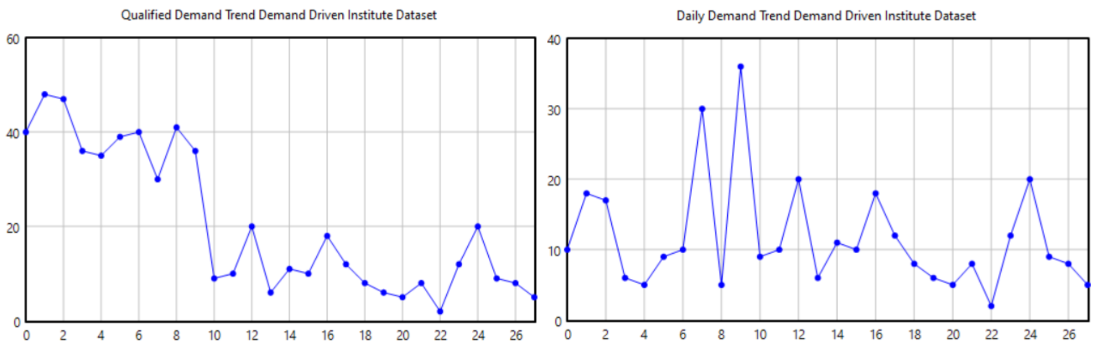


Fig. 5.59. *Qualified Demand and Daily Demand curves used to validate W-III*

t	Qualified Demand	t	Qualified Demand
0	40	14	11
1	48	15	10
2	47	16	18
3	36	17	12
4	35	18	8
5	39	19	6
6	40	20	5
7	30	21	8
8	41	22	2
9	36	23	12
10	9	24	20
11	10	25	9
12	20	26	8
13	6	27	5

t	Daily Demand	t	Daily Demand
0	10	14	11
1	18	15	10
2	17	16	18
3	6	17	12
4	5	18	8
5	9	19	6
6	10	20	5
7	30	21	8
8	5	22	2
9	36	23	12
10	9	24	20
11	10	25	9
12	20	26	8
13	6	27	5

Tab. 5.6. *DDI dataset Qualified Demand and Daily Demand curves*

The first issue to tackle for loading the DDI dataset into the model was *how to mimic its starting condition*. Fig. 5.60 provides the initial state of the system in the DDI simulation.

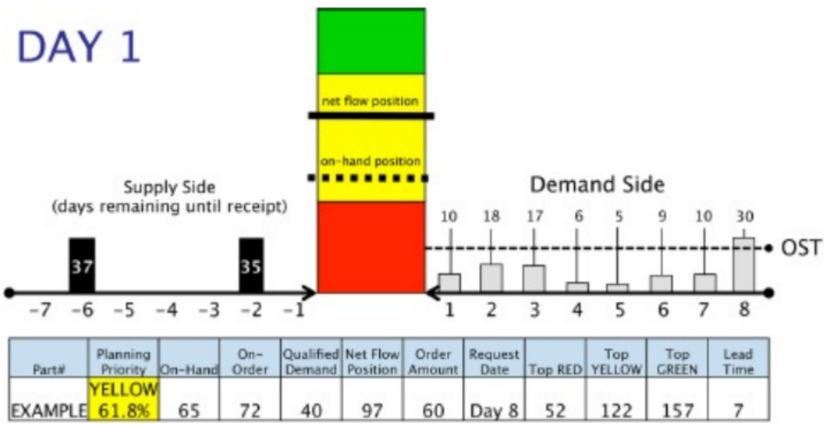


Fig.5.60. *The initial simulation condition provided in the DDI simulation dataset*

While setting parameters like MOQ, initial On-hand, LTF and DVF or Qualified Demand is straightforward exploiting Vensim capability of setting initial point values for any variable, the initial condition for variables that are defined upon more complex dynamic loops required custom modification to the model. In particular, for what regards the *in-transit quantities,* which in the proposed model are represented by the total WIP in the system (WIP + Throughput), the initial condition is defined as a *set of values to take place during a Manufacturing Lead Time cycle*. In other words, the initial condition for the throughput in the DDI example was not a single value at t=0, but rather a list of values, namely

- 35 units flowing into Finished goods inventory at t = 1,
- 37 units flowing into Finished goods inventory at t = 5

This condition was achieved by making the throughput formulation capable of selecting which input to use, choosing between the Potential Throughput Rate and the exogenous Initial Throughput Rate function, based on the current simulation time, as shown in Fig. 5.61

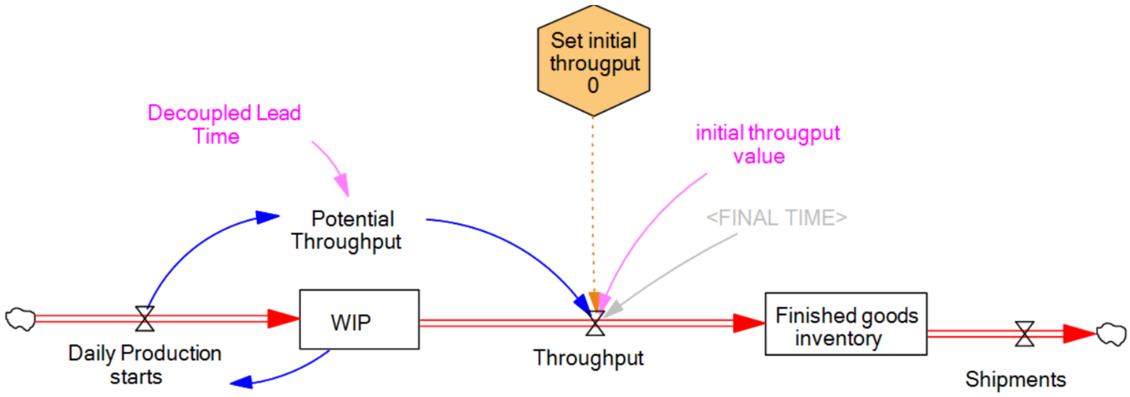


Fig.5.61. *Modification to the throughput to match DDI initial conditions*

Following the new formulations are reported

Reformulated **Throughput.** The same throughput as defined in Par. 5.3.2.1.3 but with the additional feature to override its initial condition setting.

```
Context = Endogenous          Type = Flow          UOM = units/day

Throughput. =
 (
  Set initial Throughput *
   (initial throughput value+(MAX(Potential Throughput-WIP scrapping
rate, 0) *
  ((PULSE(0,6)*0)+(PULSE(7,FINAL TIME)*1))))
 )
+
 (
   (1-Set initial throughput)*MAX(Potential Throughput-WIP scrapping
rate, 0)
 )
```

Set initial Throughput. It allows to override the Throughput initial condition set by the system feedback loops to impose a custom initial set of values.

```
Context = Exogenous      Type = Scenario          UOM = dimensionless
```

Initial Throughput Value. The custom function to override the initial Throughput behaviour.

```
Context = Exogenous      Type = Auxiliary        UOM = dimensionless
```

```
Initial throughput value =  (35 * PULSE(2,0)) + (37 * PULSE(4,0))
```

The PULSE function, which allows the creation of step stimuli of any intensity for a determined period of time-units, was extensively used. Using PULSE for triggering "point-stimulus" in the desidered dates allowed constructing the same DDI input function for throughput in the model.

Finally, slight modifications were needed in order to impose a custom value to the initial finished goods and WIP inventory target levels.

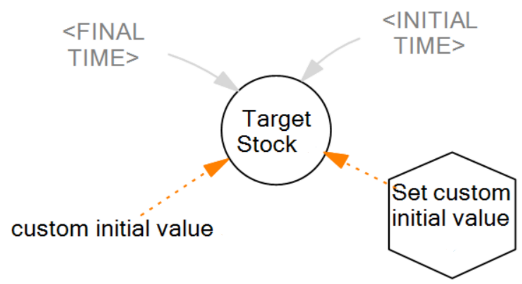


Fig.5.62. *Modification to the Target Stock to accept a custom initial value*

> ***Set Custom initial value.*** It allows to override the initial Target Stock condition with a custom exogenous value.
>
> `Context = Endogenous     Type = Scenario          UOM = dimensionless`

> ***Custom FG initial value.*** The custom initial value to set for the Finished Goods Inventory.
>
> `Context = Exogenous      Type = Constant          UOM = units`

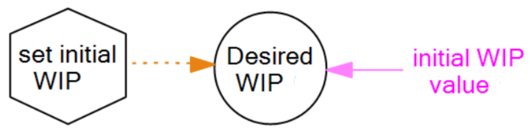


Fig.5.63. *Modification to the Desired WIP to accept a custom initial value*

Formulations for the WIP follow the same logic as above and are hereby omitted. The formulation for the Target Stock and Desired WIP are here omitted, being the impact of those additions marginal on their formulation. However, they are included in the Appendix to this study.

A final addition was required to let the model fully match with the DDI simulation, namely adding a "*quality inspection plan*" logic. Indeed, in the DDI simulation, from t=17 to t=20, 40 units are taken from the available stock-on hand to perform quality checks. In the DDMRP logic this situation is handled as an increase in the quantity in-transit for a decrease of quantities on-hand. In the proposed model this is not doable, being the quantity in transit determined by the system throughput and the current WIP. Thus an additional stock, called ***Under Quality Check*** and connected with the Finished Good Inventory Stock, was added, as shown in Fig. 5.64.

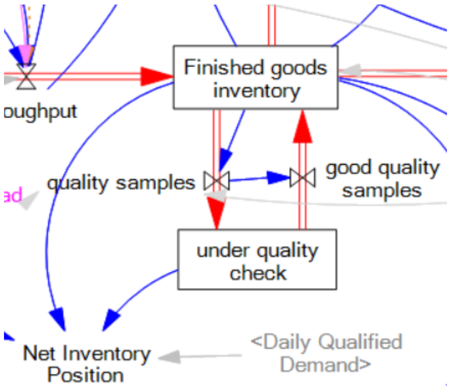


Fig.5.64. *Addition of the under quality check stock*

Under quality check. The accumulation of quantity sampled from the Finished Good Inventory for quality inspections.

```
Context = Endogenous            Type = Stock          UOM = units

Under quality check = INTEG (quality samples-good quality samples,
Under quality check, 0)
```

Quality samples. Quantity sampled from the Finished Good Inventory for quality inspections.

```
Context = Endogenous            Type = Flow           UOM = units/day

Quality samples =
 IF THEN ELSE(demand scenario=4 :AND: Decoupled Lead Time=7,
  IF THEN ELSE(Finished goods inventory>0, 40*PULSE(16,1), 0)
,0)
```

Good quality samples. The fraction of non-defective items from the sampled population of Finished Goods.

```
Context = Endogenous            Type = Flow           UOM = units/day

Good quality samples = DELAY MATERIAL( quality samples, 7, 0, 0)
```

Reformulated **Net Inventory Position.** The net inventory position as defined in Par. 5.3.3.3.1 adapted to accept quality check withdrawals.

```
Context = Endogenous             Type = Stock         UOM = orders

Net   Inventory   Position   =   (Finished   goods   inventory+WIP-Daily
Qualified Demand)+under quality check
```

As it can be seen, this part of the model formulation is specific to the DDI case only, thus *it is deactivated during other use-cases* (e.g. pieces are sampled for quality checks only when running the Demand Scenario = 4). On the other hand, taking into account quality issues, goods returns or reverse logistics in general, it is something to expect in a model oriented to productive environments, hence for this reason, the *quality inspection plan* logic is kept in the model even if not effectively utilised yet in all other demand scenarios. In this way the option to further investigate its dynamic contribution to the whole system response in the future is left open for future developments.

Table 5.6. gives all model parameter settings in order to launch the simulation.

Finished Good Inventory	**Validation W-III**	**Raw Materials Inventory**	**Validation W-III**	**S&OP**	**Validation W-III**
Productive Capacity	120.000 pcs	Avg BOM parent to child usage ratio	1 pcs/pcs	*Finished Goods Safety Stock Coverage*	14 days
Adopted Inventory Management Policy	DDMRP	*Adopted Inventory Management Policy*	MRP	*Adopted Inventory Management Policy*	DDMRP
Decoupled Lead Time	56 days	Raw Materials Safety Stock Coverage	6 days	*Impose ADU trend*	TRUE
FG Inventory adjustment time	56 days	Raw Materials Inventory Review Period	14 days	ADU trend	10 pcs/day
WIP adjustment time	14 days	Order Release Time	14 days	*Demand Variability Factor*	0.5
WIP scraps rate	0 pcs/day	Agreed Purchasing Lead Time	7 days	*Lead Time Factor*	0.5
Obsolescence Time	365 days	*Obsolescence Time*	365 days	Minimum Order Quantity	20 pcs
Set initial WIP	TRUE	**Demand Forecasting Module**	**Validation W-III**	*Desired Order Cycle*	*0 days*
Initial WIP	72 pcs	*Daily Customer Orders*	See Fig. 5.59	**Order Fulfilment Module**	**Validation W-III**
Set initial Throughput	TRUE	*Daily QUalified Demand*	See Fig. 5.59	*Customer Tolerance Time*	14 days
Initial Throughput	35 * PULSE(2,0) + 37 * PULSE(4,0)	*Time to perceive orders rate changes*	56 days	**ADU Estimation Module**	**Validation W-III**
				disabled	*disabled*

Tab. 5.6. *Parameters setting for W-III validation phase*

5.3.6.2. Discussion of the model response

Once all inputs were loaded, the model responded as shown in Fig.5.65. The model re-proposed the same trends for *Net Flow Position* and *On-Hand Inventory* presented by the authors of DDI simulation. On top of those, all aforementioned metrics have been also computed, showing something new about the DDI simulation. The capability to provide a large panel of metric on each run is considered one of the model's main strengths, making it attractive for inclusion in real S&OP processes.

The positive outcome of this validation step worked as an essential "*acid-test*" prior to embark into the final validation of the model against the Whirlpool case study, knowing at this point that the underhood DDMRP model logic already proved trustworthy in other - even if extremely simplified - contexts.

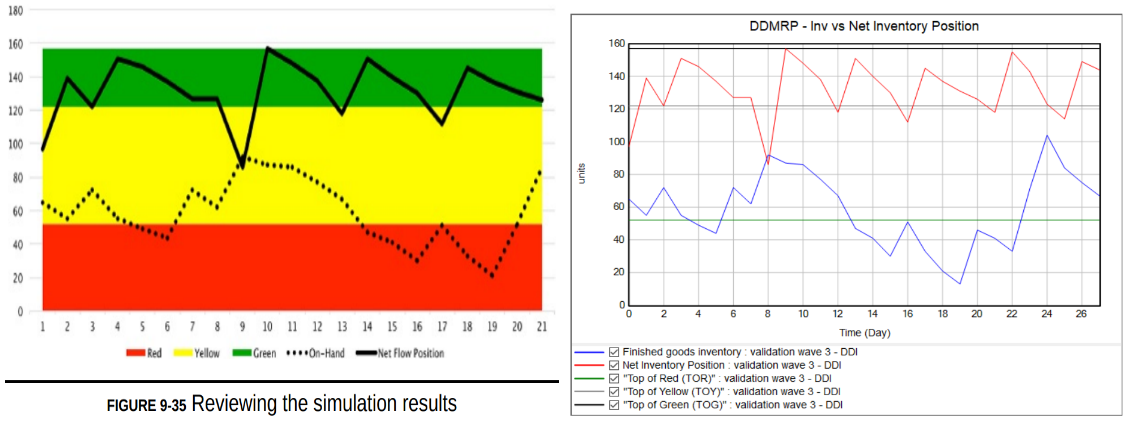
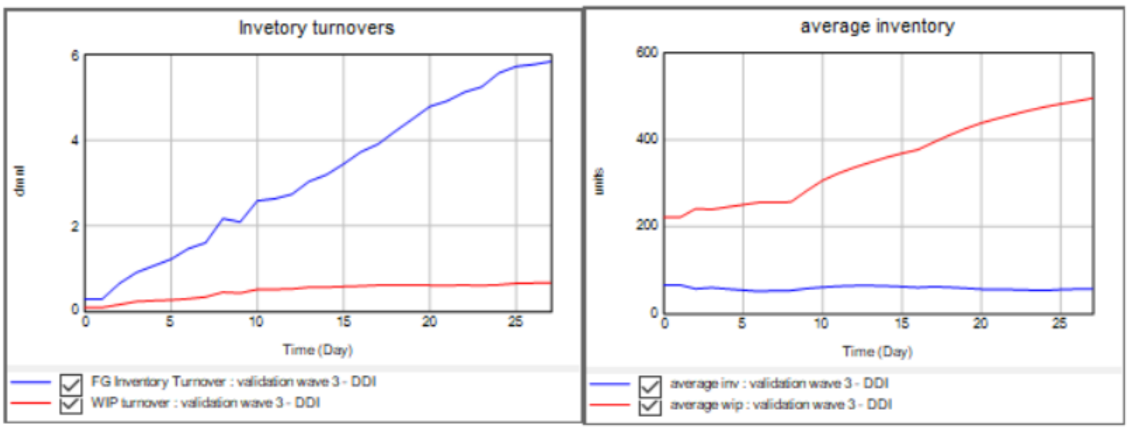


Fig.5.65. *Side-by-side comparison of DDI simulation results with the proposed model response*



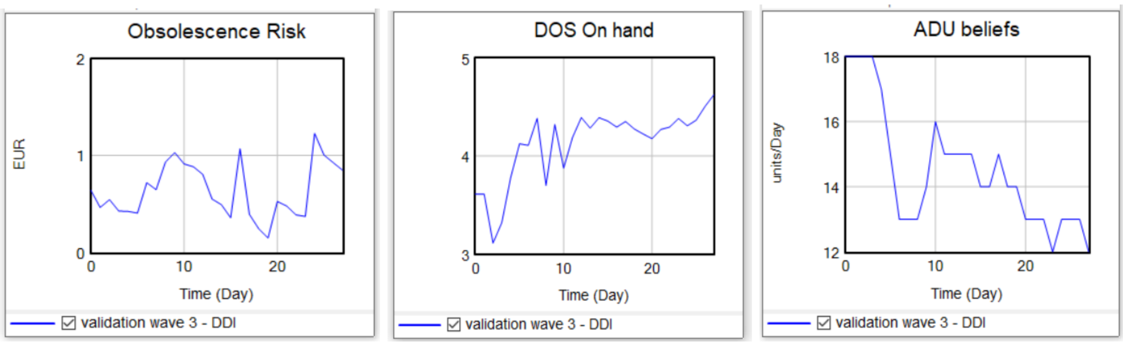


Fig.5.66. *Additional metrics computed by the proposed model about the DDI example*

5.3.7. Sensitivity Analysis of the final model

5.3.7.1. The effect of capacity bottleneck

Before embarking into validating the model against the case study dataset, it was of interest to the modeller to briefly review the system response generated by the different inventory management policies under the same harsh conditions used in Par. 5.3.2.3, by comparing some of the main model KPIs. Fig. 5.66 presents the model response under either the DDMRP configuration and the base configuration. As reported by other authors, there is no such "one size fits all" regarding inventory management policies so declaring an absolute winner among the considered policies is not the real scope of this study. At a first sight is evident that there exists "performance overlappings" for the twos under many KPIs, but a general overview seems to suggest that

1. **DDMRP heavily suffers when a capacity bottleneck is introduced.** Being the net flow equation logic impeding continuous release of production orders, the average size of the downstream orders is larger than in the base model. If a capacity bottleneck hits on order release, the buffer will not be replenished as planned. On the other hand, the base model formulation assumes orders of any size can be released without taking into consideration economies of scales.

2. **DDMRP requires a greater use of productive capacity to run smoothly and prevent excess accumulation.** This result goes in contrast with what many authors found, namely a lower WIP in DDMRP configurations. It must be noticed that DDMRP is getting compared to a model where continuous replenishment is allowed whereas DDMRP seems to generate a discrete stream of large lumpy orders downstream when under stress.

3. **Both policies yielded the same service level trend but customer satisfaction differs substantially**. Once the finished good inventory is stocked-out due to the capacity bottleneck in the DDMRP configuration, the rather lumpy replenishment rule produces "no-throughput gaps" where no orders are fulfilled at all due to the discrete gap in the throughput flow, as shown in Fig.5.67. Hence, all orders in those

gaps are likely to be cancelled. Once those are cancelled, the replenishment quantities arriving in dela, stock as excesses.

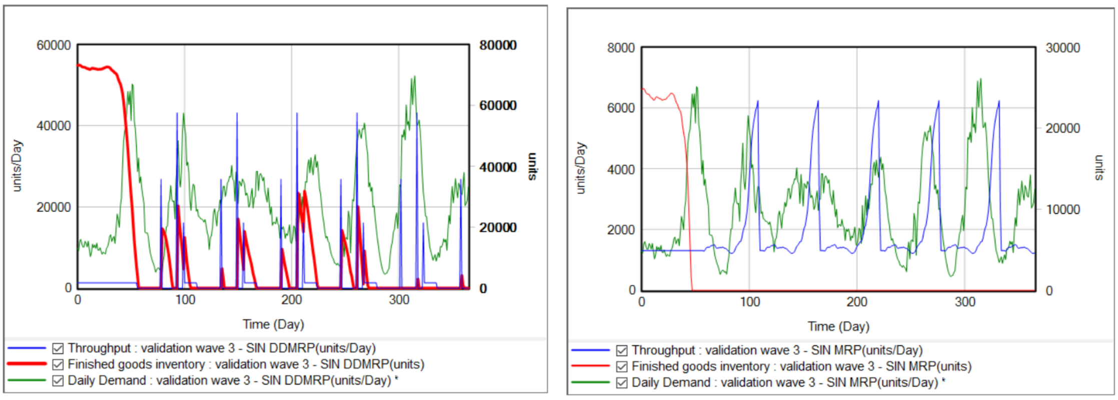
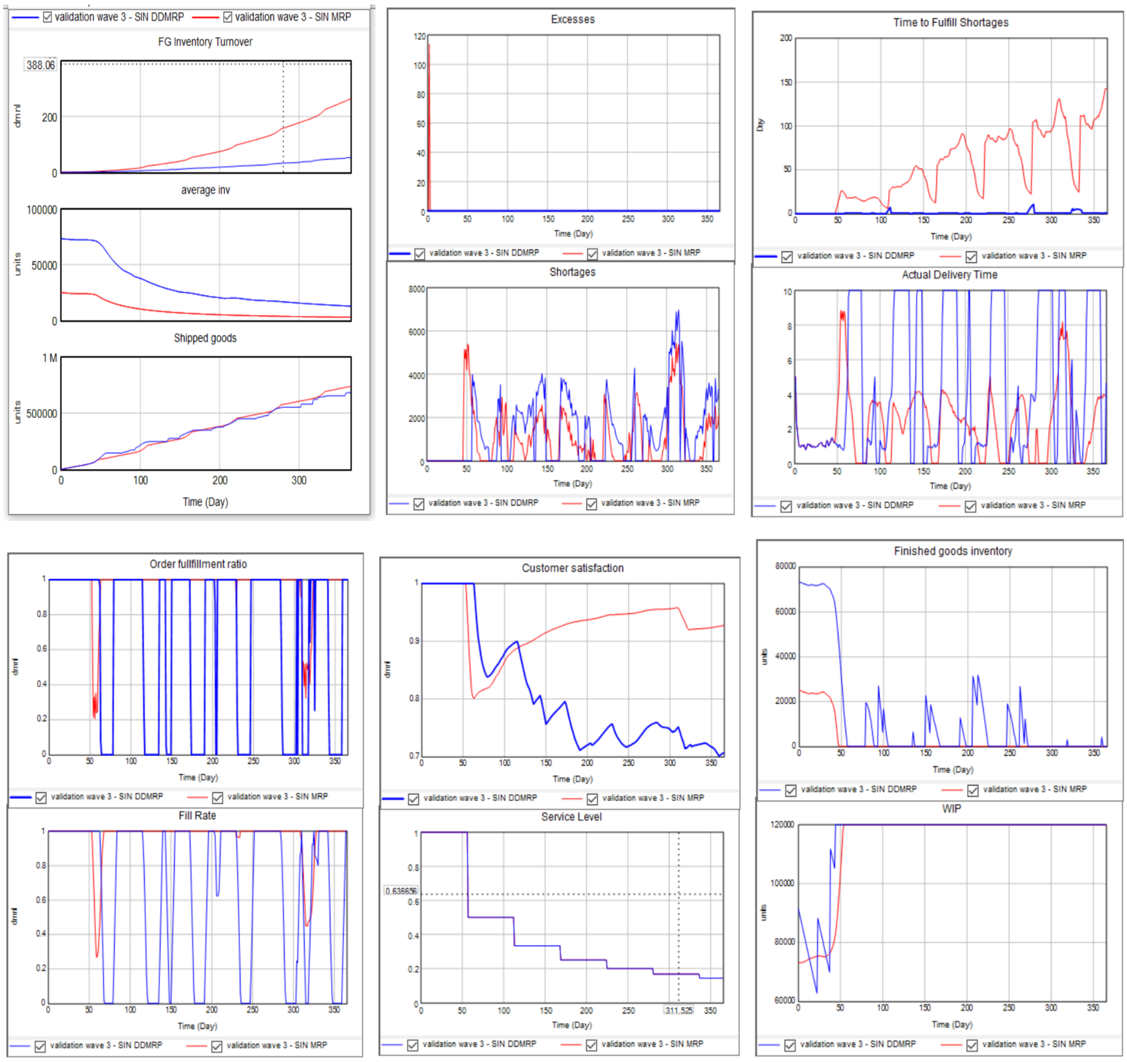


Fig.5.67. *Throughput gaps inducing higher order cancellation in DDMRP environments*



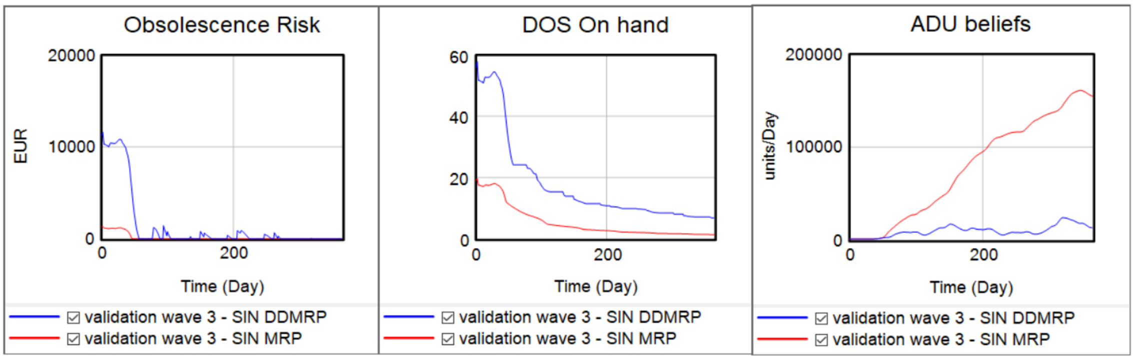


Fig.5.66. *Sterman model versus DDMRP model under extreme testing conditions*

	mean BASE	mean DDMRP	std. dev. BASE	std. dev. DDMRP
Fill Rate	0.97	0.66	0.13	0.43
Daily Fill Rate	0.13	0.41	0.33	0.48
Finished goods inventory	2,795	12,798	7,500	23,411
Throughput	1,952	1,663	1,319	6,216
WIP	114,034	115,434	14,929	13,135
Orders on Allocation	86,604	8,331	56,078	9,230
Cancelled Orders	33,319	116,870	19,050	90,032
Order fullfillment ratio	0.97	0.66	0.13	0.47
Target Stock	46,943	560,121	9,544	323,683
Desired WIP	182,480	700,152	44,190	404,604

Table. 5.7. *Side-by-side comparison of Base Case vs. DDMRP simulation under extreme stress-testing conditions*

Based on these first insights, a *univariate sensitivity analysis* was performed to study the effect of the capacity constraint on the DDMRP performance. 10000 simulations over a time horizon of 10 years were run for both model configurations. The productive capacity was set to be varying in a range from 0 to 2M pcs in order to cover most of the spectrum, while DLT was kept to 56 days so as to simulate a worse-case scenario of an SKU made by components procured overseas. The input demand signal was as in Fig. 5.67. What seems to emerge is an extremely high dependency of DDMRP performance, measured in terms of total inventory levels and WIP utilisation, when a capacitated system is considered. Indeed, when a stock-out hits in a saturated system, DDMRP starts triggering large replenishment orders as long as the NFP stays below zero. Such *batch orders* are repeated at each iteration while the decoupled position is stocked out, ***accumulating orders as big as the entire maximum DDMRP buffer size* (TOY+GZ) *in the inventory supply line***. If stockouts occur while demand is rising, the situation get worse and worse, always releasing bigger batch orders, leading to the situation shown in Fig. 5.68. This behaviour is seen by the author as a clear representation of the penetration of Bullwhip oscillations within the decoupled position through the downstream nodes. This **overactive behaviour** seems instead not affecting the response of the base Sterman model, being the mechanism of control of the supply line in place.

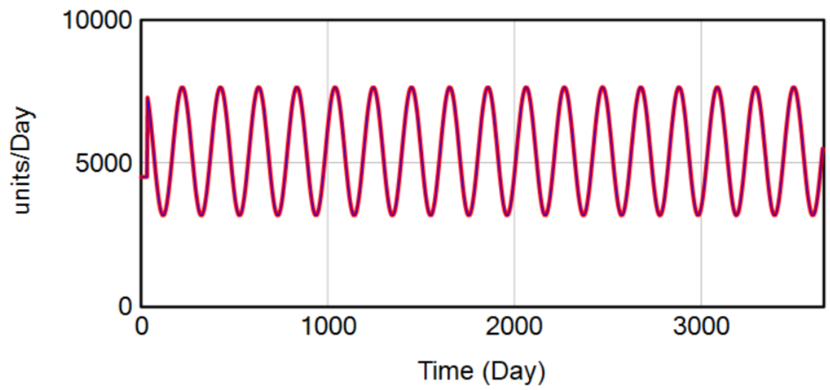


Fig.5.67. *The input demand trend used during to assess the effect of Productive capacity on the model*

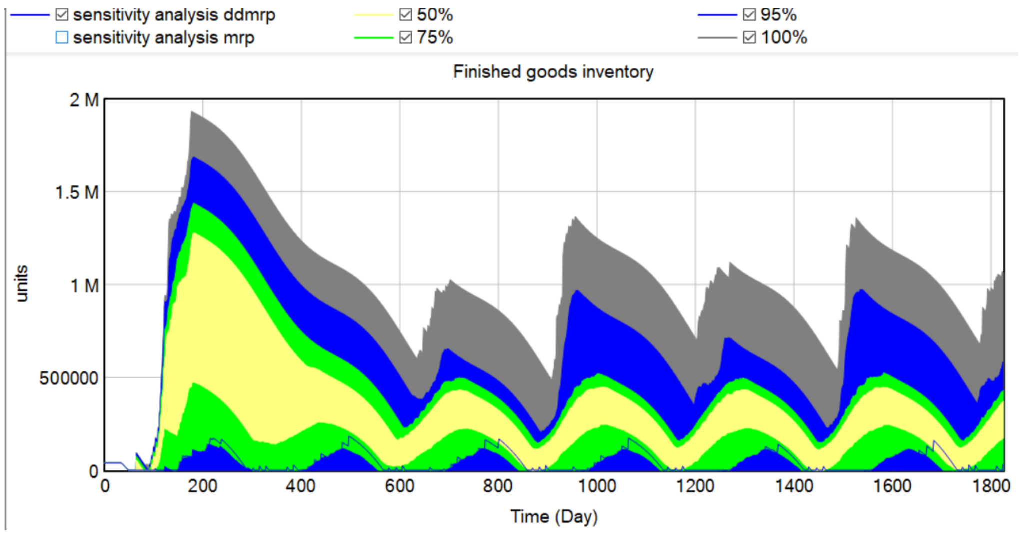


Fig.5.68. *Proposed model Finished Good Inventory reaction to capacity bottleneck*

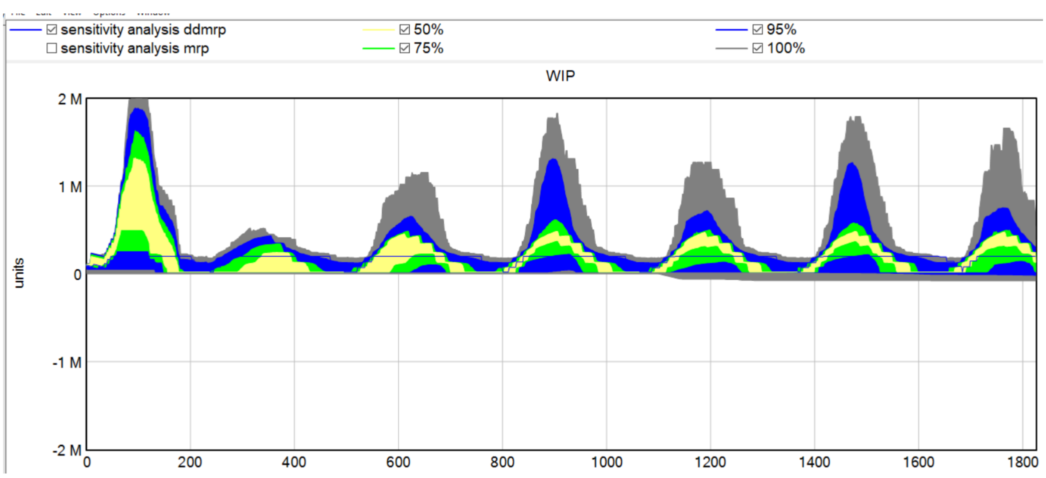


Fig.5.69. *Proposed model WIP reaction to capacity bottleneck*

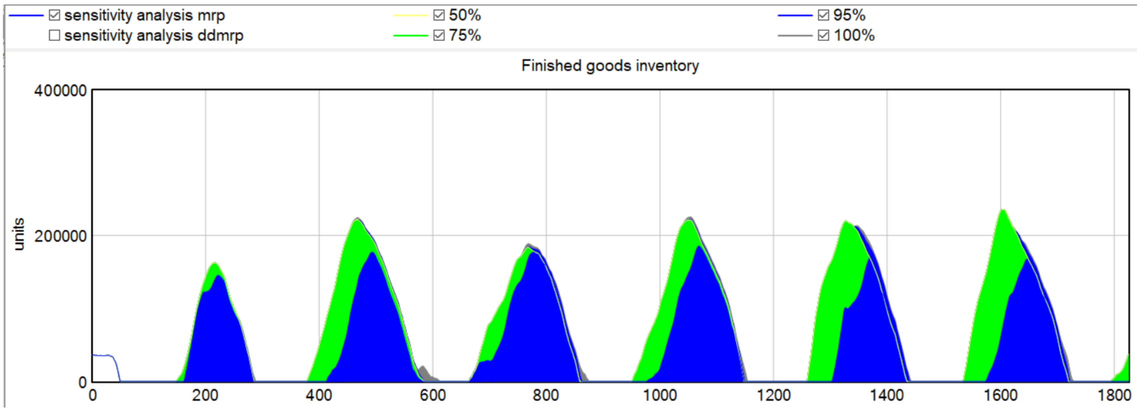


Fig.5.70. *Sterman model Finished Good Inventory reaction to capacity bottleneck*

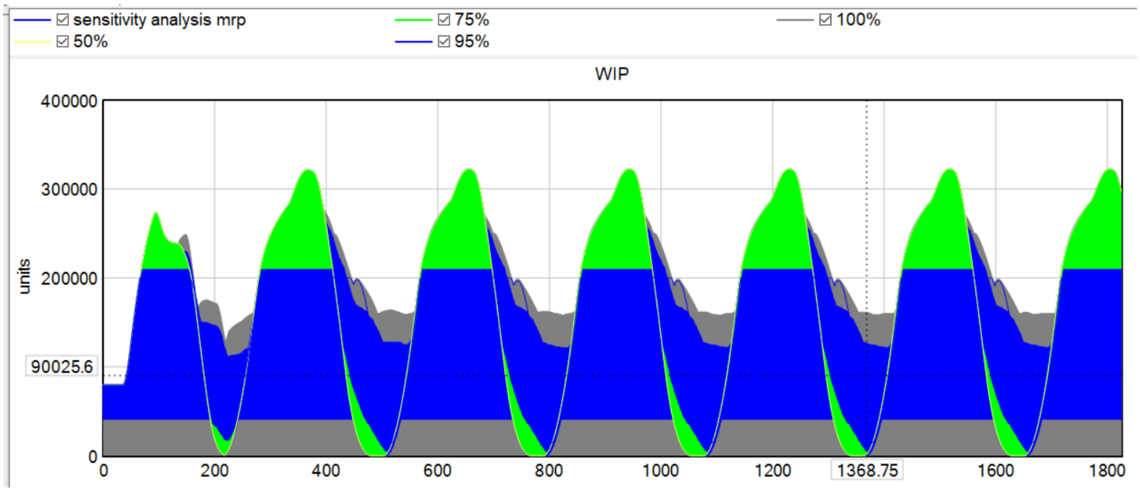


Fig.5.71. *Sterman model WIP reaction to capacity bottleneck*

5.3.7.2. The effect of LTF and DVF on DDMRP performance

In order to answer to RQ3, a simple multivariate sensitivity analysis was run for the DDMRP configuration while letting varing DVF and LTF between the ranges indicated for a Purchased Item with Short Lead Time (DLT=1). Thus DVF ∈ [0, 1] whereas LTF ∈ [0.6, 1].

The same input demand trend used in Par.# was used for this simulation. The resulting model response for the Finished Good Inventory levels is shown in Fig.5.72 it can be seen that the inventory fluctuate heavily, peeking up to 30.000 units / day.

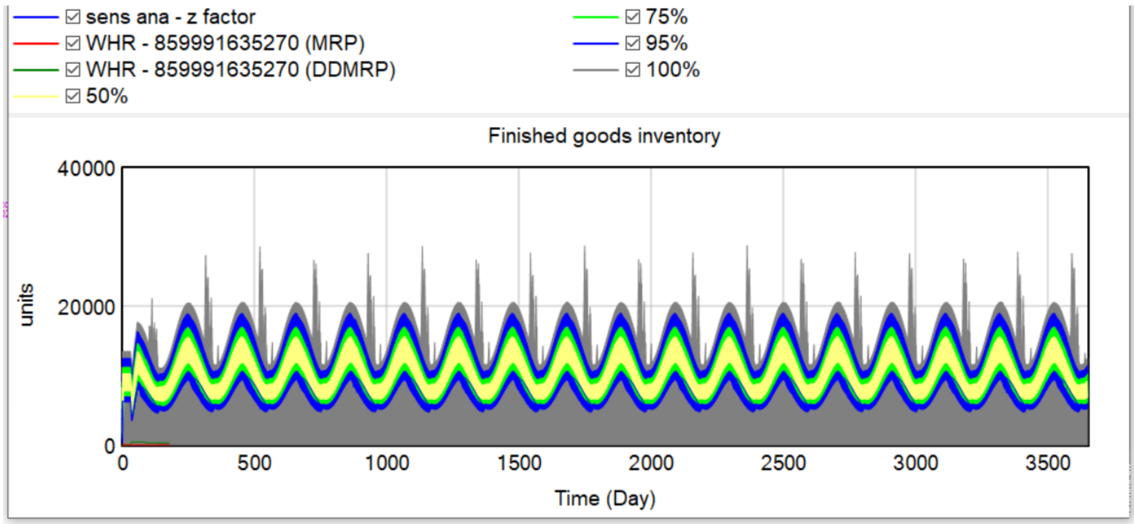


Fig.5.72. *Effects of DVF and LTF on the Finished Goods Inventory levels*

Chapter 6

Model validation against Whirlpool inventory data

In Chapter 5 the *rolling-wave development* approach deployed to derive the final full-fledged model was described. In the following Chapter such a model is finally tested against the real case study data in order to see what results it returns and whether they fit with the historical data.

6.1. Finished goods selection

While the DDMRP methodology is applicable to multiple SKU environments by simply exploding and adding the top-end requirements's ADU on all shared components, the proposed model focuses instead on single SKUs, exploiting the caveats introduced in Sterman to consider components availability without duplicating the Raw Materials module for each branch in the BOM.

Moreover, the proposed model was idealised as to be a tool for rapidly benchmarking S&OP scenarios while relying on an accurate but "high-order" view of inventory. On the other hand, the Whirlpool working environment is determined by parallel production of multiple products, having in its portfolio both high-runner and slow-movers goods. Thus, limiting the proposed model to single SKUs analysis would mean purposely discarding all those dynamics generated by *capacity cannibalization* between "competing SKUs" produced in the same plant, in terms of shared raw-material, components or machine-time.

Hence, a reasonable trade-off between model accuracy and reality representation requires considering a panel of SKUs so as to cover all typical finished goods categories present in the Cassinetta plants portfolio. The ABCXYZ matrix was the tool used to guide this step, determining 3 representative classes:

Flagships. Goods presenting very high-volumes with very low variability, thus all items belonging to the AX-class. Those goods drive most of the sales, their demand is easily forecasted and thus very high service-levels must be always assured to them at any cost. This goods represents the typical "JIT example" where dedicated capacity is assigned only for their production.

Nervous. Goods presenting medium-to-low volumes with very high variability, thus all items belonging to the BZ-class. Those goods represent a threat to flagships, being their volumes not as low as to not impact flagships production schedule plans. Moreover, their management complexity is increased by their highly volatility of volumes which make their forecasts unreliable, thus nervousness in their production schedule is foreseen. Items with high unit costs represent a double threat.

Customs. Goods presenting low volumes with very high variability, thus all items belonging to the CZ-class. Those goods present lumpy demand that suddenly creates a production requirement, stealing potential capacity to flagships. A typical example of customs are built-in kitchen bundles required by big wholesalers like IKEA.

The proposed segmentation of SKUs can be seen for the model purposes as *flagships protection being the overall goal of the system getting distrubed by other SKUs requirements*.

For each of the three classes the most representative SKUs (as of time of extraction) were selected, basing the selection on the DCM for flagships and Unit Costs for the rest. Being the model "plant-based", a hard selection criteria was that all selected SKUs were produced in the same plant.

While further customisations to the model so as to address parallel production dynamics were not planned for this study, the decision of considering benchmarking the model upon multiple SKUs types is a first step toward that direction. The extraction was performed by querying the L2 level of the DP directly so as to extract the overall ABCXYZ matrix grouped by plants, something apparently missing at the time in the DP (Fig. 6.1). From it the selected SKUs with the matching characteristics described above were

Flagship :	**859991602220**	(Cassinetta REF)	AX with max DCM in last 6 months
Nervous :	**859991551170**	(Cassinetta CKG)	BZ with max unit cost in last 6 months
Customs :	**859991635270**	(Cassinetta REF)	CZ with max unit cost in last 6 months

emea_category	cluster	plant	plant_desc	up_down_flag	AX	AY	AZ	BX	BY	BZ	CX	CY	CZ
LAUNDRY	CENTRAL EUROPE	C060	HQ Comunanza FDC (FG)	UPSTREAM	0	0	**24**	0	0	**2**	0	0	**5**
LAUNDRY	FRANCE	C060	HQ Comunanza FDC (FG)	UPSTREAM	0	0	17	0	0	2	0	0	0
LAUNDRY	NORTHERN EUROPE	C060	HQ Comunanza FDC (FG)	UPSTREAM	**1**	0	12	0	0	1	0	0	0
COOKING	ITALY	C020	HQ Cassinetta FDC (FG)	UPSTREAM	0	0	**10**	0	0	**1**	0	0	0
COOKING	NORTHERN EUROPE	C020	HQ Cassinetta FDC (FG)	UPSTREAM	0	0	19	0	0	1	0	0	**4**
COOKING	FRANCE	C021	HQ Cassinetta CDC (FG)	UPSTREAM	0	0	43	0	0	3	**1**	0	5
REFRIGERATION	RUSSIA	C021	HQ Cassinetta CDC (FG)	UPSTREAM	0	0	**3**	0	0	0	0	0	0
REFRIGERATION	CENTRAL EUROPE	C021	HQ Cassinetta CDC (FG)	UPSTREAM	0	0	33	0	0	**4**	**1**	4	**7**
REFRIGERATION	NORTHERN EUROPE	C021	HQ Cassinetta CDC (FG)	UPSTREAM	0	0	2	0	0	0	0	0	0
REFRIGERATION	ITALY	C020	HQ Cassinetta FDC (FG)	UPSTREAM	0	0	**22**	0	0	**2**	0	0	**4**
REFRIGERATION	NORTHERN EUROPE	C020	HQ Cassinetta FDC (FG)	UPSTREAM	0	0	19	0	0	2	0	0	1
REFRIGERATION	IBERIA	C020	HQ Cassinetta FDC (FG)	UPSTREAM	0	0	6	0	0	0	0	0	0
DISHWASHING	NORTHERN EUROPE	C281	PL - Radomsko CDC	UPSTREAM	0	0	**55**	0	0	**6**	0	0	**6**
DISHWASHING	ITALY	C281	PL - Radomsko CDC	UPSTREAM	0	0	53	0	0	6	0	0	0
DISHWASHING	CENTRAL EUROPE	C281	PL - Radomsko CDC	UPSTREAM	0	**2**	85	1	3	14	**1**	8	28

Fig. 6.1. *The reconstructed global ABC-XYZ classification by plant*

The codes introduced above represent the SKUs ID used by GSS to track each item. While GSS analysts usually do not use additional metadata to elaborate information about SKUs, and thus they are also not required in the proposed model, for clarity to the reader following it is provided "what these products really are".

859991602220 : Build-In Fridge and Freezer SP40 801 SPACE 400 Line

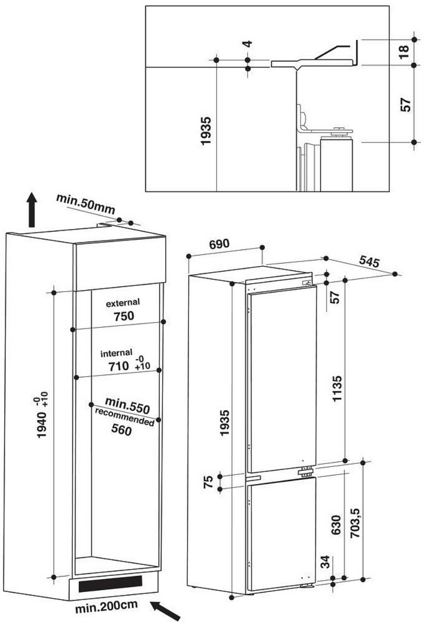


Fig.6.2. *Product images and dimensions of 859991602220*

859991551170 : Build-In Double Ovens and Steam Ovens W9 OS2 4S1 PW STEAM (Line 4)

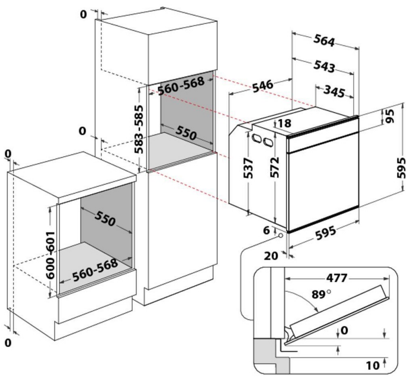


Fig.6.3. *Product images and dimensions of 859991551170*

859991635270 : Build-In Fridge and Freezer WHC20 T593 P CB Electric Thunder Line

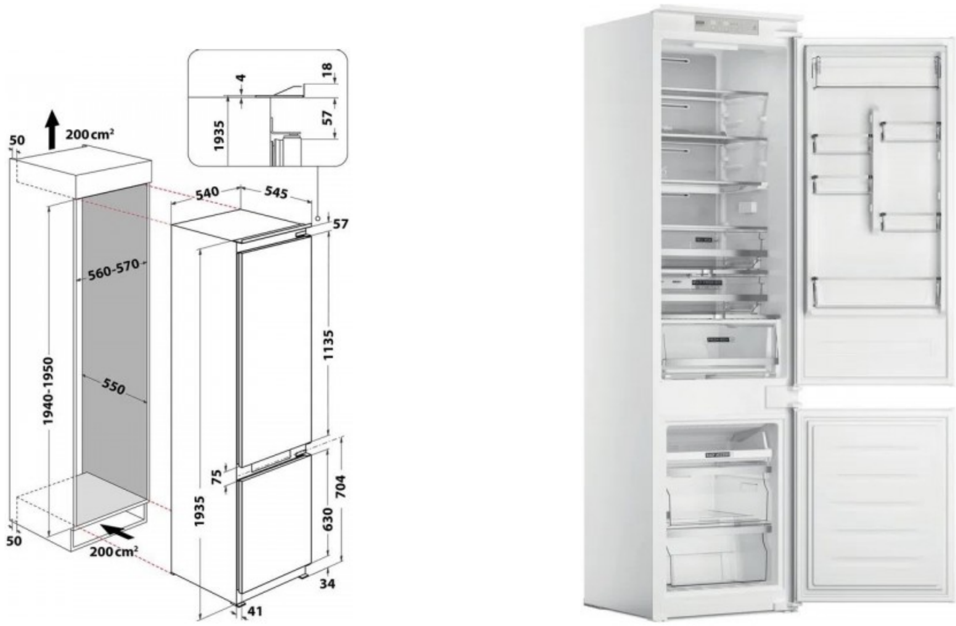


Fig.6.4. *Product images and dimensions of 859991635270*

6.1.1. Historical data extraction

An extensive review of the Whirlpool inventory Google Cloud data-platform (DP) was given in Chapter 2. To retrieve from it all the data required, a detailed reverse-engineering activity has been performed to understand how all SQL-tables (more than 200) used to work together, in which sequential order they got updated, which were deprecated or outdated and which instead were only used for development or testing purposes. Google BigQuery provides a set of "metadating queries" that can be launched against the DP datasets to retrieve all their information, like the list of all the included tables ordered by creation date and last-update date. Those queries were exploited to filter out the non-relevant SQL-tables and have an idea of the updating time-schedule of each of those.

A custom SQL-procedure has been devised in order to extract from the DP all required data for the SKUs in scope. The queried data-sources were reviewed as much as possible with the GSS analysts. The procedure takes 5 input parameters:

- The target SKU,
- The Simulation Start Date,
- The Simulation End Date,
- A boolean value to decide whether data must be aggregated by plant or kept separate

and returns the following data for each SKU:

- Material code ID,

- Historical date of reference,
- relative timestamp from simulation start date,
- daily forecasted demand trend,
- daily qualified demand
- daily net flow position
- total target inventory
- average daily usage
- on hand usable quantity (net of bad stock)
- in-transit quantity
- red zone
- yellow zone
- green zone

One of the main advantages of having a procedure for data retrieval, aside from its speed, is that it can manipulate the data directly from the sources and pre-format them as needed to ease in their final use, namely loading them in Vensim. This is done by computing the relative simulation timestamp to which data in each row are referred to, or allowing aggregation of all values by plants. The data-series which "sets the clock" are the demand forecasts, without which it is impossible to compute qualified demand and run the model. Thus the minimum date available of demand sets the zero of the simulation, whereas the last demand input flags its end. Moreover, as clear by their name, devising a procedure for data retrieval is basically the same done when planning systematic literature review, establishing *a literature review protocol:* it standardises the data-retrieval process, documenting it for future assessment, needs or modellers.

material	plant	YEAR	ISOWEEK	d_date	cod_argument	value	rel_timestan
859991602220	Cassinetta Site	2021	36	2021-09-06	adu	44.33230769	0
859991602220	Cassinetta Site	2021	36	2021-09-06	intransit_qty	0	0
859991602220	Cassinetta Site	2021	36	2021-09-06	gr_zone	383	0
859991602220	Cassinetta Site	2021	36	2021-09-06	on_hand_usable_qty	188	0
859991602220	Cassinetta Site	2021	36	2021-09-06	tot_target_inv	192	0
859991602220	Cassinetta Site	2021	36	2021-09-06	red_zone	0	0
859991602220	Cassinetta Site	2021	36	2021-09-06	yl_zone	399	0
859991602220	Cassinetta Site	2021	36	2021-09-06	daily_demand_trend	94.16666667	0
859991602220	Cassinetta Site	2021	36	2021-09-07	gr_zone	388	1
859991602220	Cassinetta Site	2021	36	2021-09-07	tot_target_inv	195	1
859991602220	Cassinetta Site	2021	36	2021-09-07	adu	44.51692308	1
859991602220	Cassinetta Site	2021	36	2021-09-07	red_zone	0	1
859991602220	Cassinetta Site	2021	36	2021-09-07	intransit_qty	0	1

Fig.6.5. *The extracted dataset from the SQL-procedure*

The procedure is reported in the appendix of this paper, after some privacy changes in the table names have been done. The extraction was done on 2022-02-23 by setting the SQL-procedure to retrieve all data available between 2021-01-01 and 2023-12-31. This data range should cover all the data visibility on the DP (Chap.3). As it can be seen in Tab.#, no data was found after 2022-02-27. Moreover, **not all series are included within the same**

boundaries. Indeed, while data about SAP historical inventory levels are daily available since the first release of the DP (June 2021) and cannot reasonably go into the future, the data retrieved about demand forecasts starts only from September 2021. A further restriction to the range is then imposed by the Daily Qualified Demand trends, which were introduced in the DP from the beginning of December 2021, **constraining the number of usable days of data to run the simulation to only 83**. The Daily Demand trend range determines the time-zero position, set at 2021-09-06.

material	*DATA TYPE*	DATE MIN	DATE MAX	TIMESTAMP MIN	TIMESTAMP MAX	DAYS AVAILABLE
859991551170	daily_qual_demand	2021-12-02	2022-02-23	87	170	83
	daily_net_flow_pos	2021-12-02	2022-02-23	87	170	83
	daily_demand_trend	2021-09-06	2022-02-27	0	174	174
	yl_zone	2021-06-20	2022-02-23	-78	170	248
	tot_target_inv	2021-06-20	2022-02-23	-78	170	248
	red_zone	2021-06-20	2022-02-23	-78	170	248
	on_hand_usable_qty	2021-06-20	2022-02-23	-78	170	248
	intransit_qty	2021-06-20	2022-02-23	-78	170	248
	gr_zone	2021-06-20	2022-02-23	-78	170	248
	adu	2021-06-20	2022-02-23	-78	170	248
859991602220	daily_qual_demand	2021-12-02	2022-02-23	87	170	83
	daily_net_flow_pos	2021-12-02	2022-02-23	87	170	83
	daily_demand_trend	2021-09-06	2022-02-27	0	174	174
	yl_zone	2021-06-20	2022-02-23	-78	170	248
	tot_target_inv	2021-06-20	2022-02-23	-78	170	248
	red_zone	2021-06-20	2022-02-23	-78	170	248
	on_hand_usable_qty	2021-06-20	2022-02-23	-78	170	248
	intransit_qty	2021-06-20	2022-02-23	-78	170	248
	gr_zone	2021-06-20	2022-02-23	-78	170	248
	adu	2021-06-20	2022-02-23	-78	170	248
859991635270	daily_qual_demand	2021-12-02	2022-02-23	87	170	83
	daily_net_flow_pos	2021-12-02	2022-02-23	87	170	83
	daily_demand_trend	2021-09-06	2022-02-27	0	174	174
	on_hand_usable_qty	2021-07-13	2022-02-23	-55	170	225
	intransit_qty	2021-07-13	2022-02-23	-55	170	225
	yl_zone	2021-07-06	2022-02-23	-62	170	232
	tot_target_inv	2021-07-06	2022-02-23	-62	170	232
	red_zone	2021-07-06	2022-02-23	-62	170	232
	gr_zone	2021-07-06	2022-02-23	-62	170	232
	adu	2021-07-06	2022-02-23	-62	170	232

Tab. 6.1. *The date ranges of all series in the extracted datasets*

Fig. 6.6 visualises the extracted dataset plotting each series over time. While stock quantities and DDMRP buffer thresholds trend were verifiable against official Whirlpool, the accuracy of the data retrieved about Daily Demand, Daily Qualified Demand and Net Flow Position was heavily doubted instead. For these, no official report was indeed yet published, denoting the probable still on-going development of the metrics. Indeed, while the relationship between Daily Qualified Demand and Net Flow Position seems reasonable (when demand rises, net flow lowers), the order scale of the values do not match with the daily demand. Even the Stable Flagship, which should rarely present qualified demand spikes, instead presents a qualified demand that averages around 4000 units/day, while its daily demand spikes once at around 200 units /day. Thus, being the Whirlpool order spike horizon at best 60 days (for Z components the ADU window is shifted 8 weeks in the future), this data seems not correct. By reconstructing the planning and execution typical DDMRP views, it can be seen that

1. **Whirlpool still does not manage SKUs planning using DDMRP**. This can be seen by the Net Flow Position which is never included within [TOR, TOY] and does not follow the reorder logic seen in Chap.2. At all effects, **Whirlpool uses DDMRP only to bisect current inventory levels into TOR, TOY, TOG and determine from this whether materials are in excess or shortage**.

2. The AX component historical inventory levels seem rather to present AZ lumpy demand instead, fluctuating rapidly between 800 and 150 units /day.

3. All selected SKUs do not have an active RZ.

A second doubtable point was on *SKUs Lead Times.* As reported in Tab.#, all SKUs seem to require **10 days of lead time** in order to complete manufacturing. *This value seems highly inflated*, considering the kind of industry in which Whirlpool operates and the price it sells its products. **The insight in Tab.# repropose the urgency of the *massive data cleaning phase* as introduced in Chap.3**, where lead-times had been identified as the main bleeding point to attack to improve the quality of the final decisions.. Finally, the MOQs seem quite low, even for the Flagship.

MATERIAL	Lead Time	moq	oct	dvf	ltf	red_zone
859991551170	10	9	1	0.8	0.5	0
859991602220	10	8	1	0.3	0.5	0
859991635270	10	8	1	0.8	0.5	0

Tab. 6.2. *Doubting values of Lead Time and MOQs*

Many could be the reasons behind those issues, foremost *an author error in reverse engineering the DP seems the most likely cause,* considering the scale of the DP that required outsourcing the project to an external consultancy company to build. For example, the way in which the ABC-XYZ matrix was reconstructed by plant might be not appropriate. On the other hand, the DP project is continuously updated thus the data retrieved might be affected by still on-going developments, such as for the Daily Qualified Demand and Net Flow Position. Unfortunately it was not possible to deeply review those data with GSS analysts due to the emergence of the contingent situation of the Ukrainian conflict. Thus, the quality of the following results must be doubted.

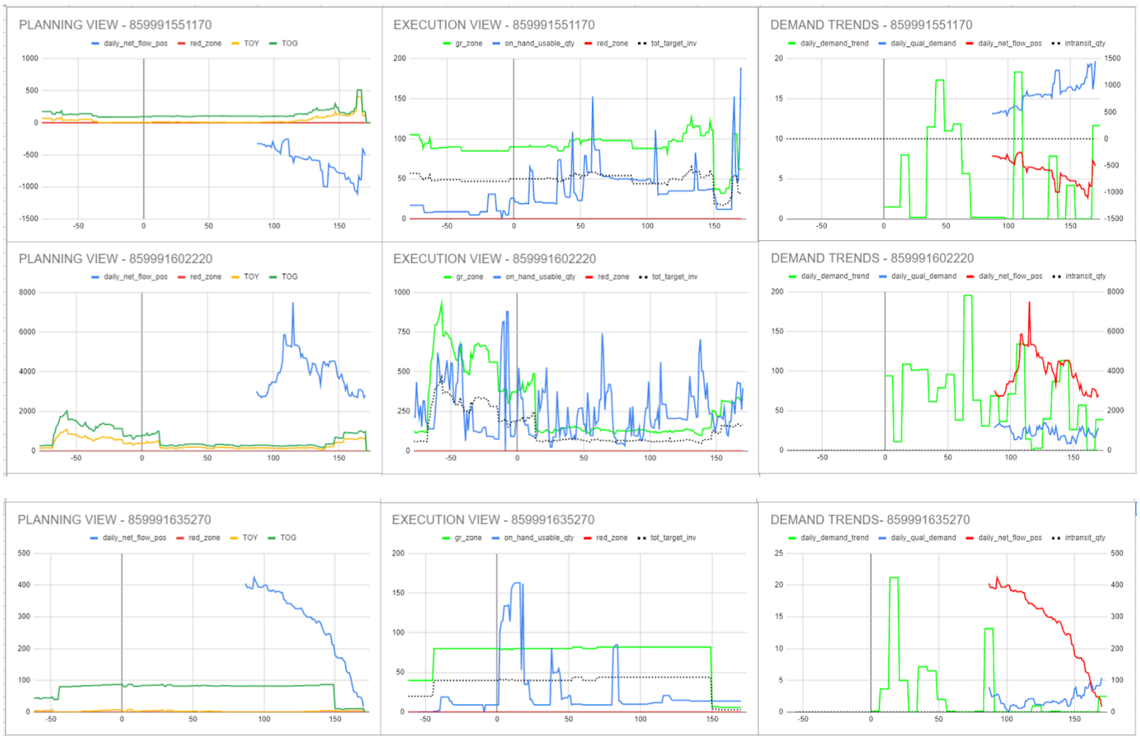
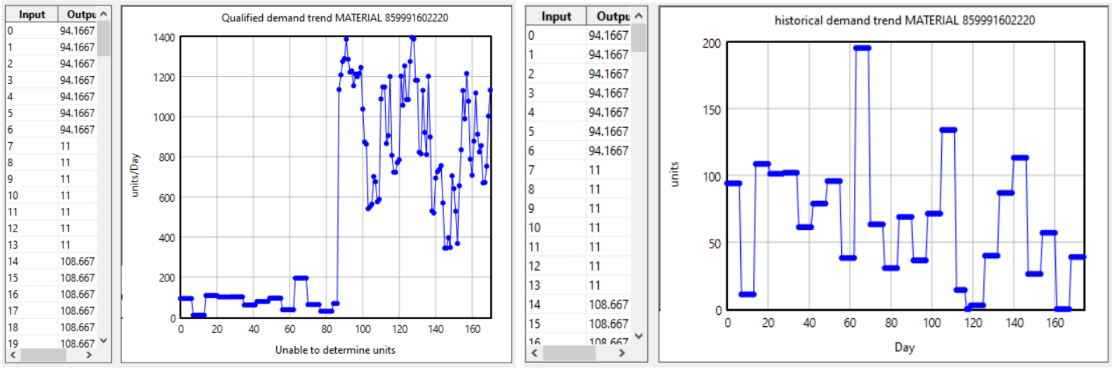


Fig.6.6. *The extracted dataset visualised*

6.1.2. Fitting historical trends under MRP setting

To load Whirlpool demand data into Vensim, a short Python script reads the table provided by the procedure mentioned above and builds a text string properly formatted so that the software can translate it into a Lookup function. The Lookups can be selected as demand inputs as seen in Chap.5. Following the model inputs are presented for all selected SKUs. Following the model runs against those inputs is presented. For all cases, *Customer Tolerance Time has been set to 7 days*. This value was estimated by reviewing Whirlpool online website where product sale is provided included with a house delivery to the house door and installation within a week. As said above, the historical data have been compared with the model running under a non-DDMRP setting. As expected, **no correspondence between the historical trends and the model output can be found even only by a qualitative look**. Some convergence can be seen in the Net Flow Position trends instead. Such result, even if extremely dismal, pinpoints the need to investigate more on possibly omitted important variables and their feedback loops, in conjunction with an improved validation of the data extraction procedure. In this regard, it is suspected that a still-ongoing *data cleanup* phase held by Whirlpool DP managers is affecting the quality of the extracted data.

Because of such results, **it was not possible to simulate additional scenarios**.



MATERIAL	Lead Time	moq	oct	dvf	ltf	red_zone
859991602220	10	8	1	0.3	0.5	0

Fig. 6.7. *Input data for 859991602220*

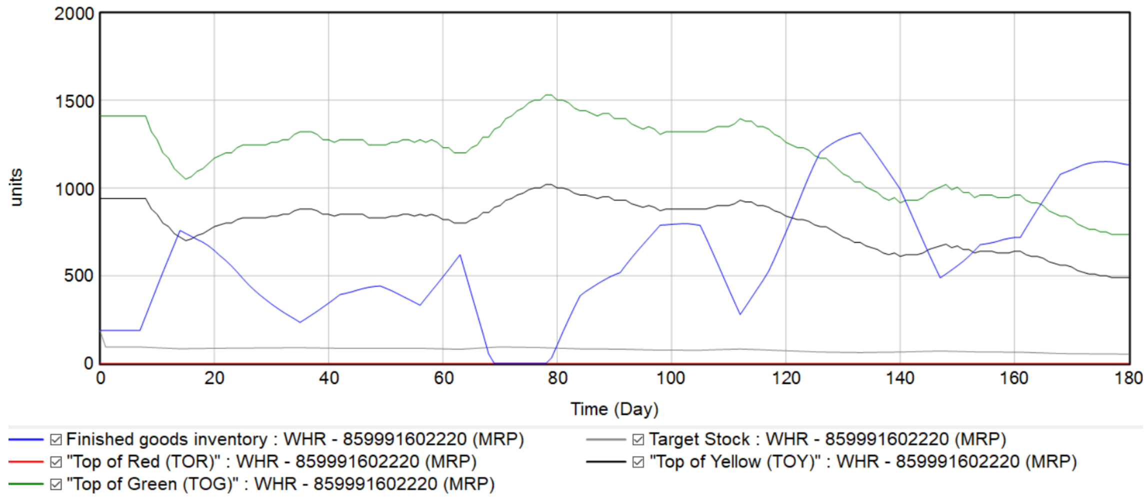


Fig.6.8. *Model Finished Goods Inventory for 859991602220 under MRP-setting*

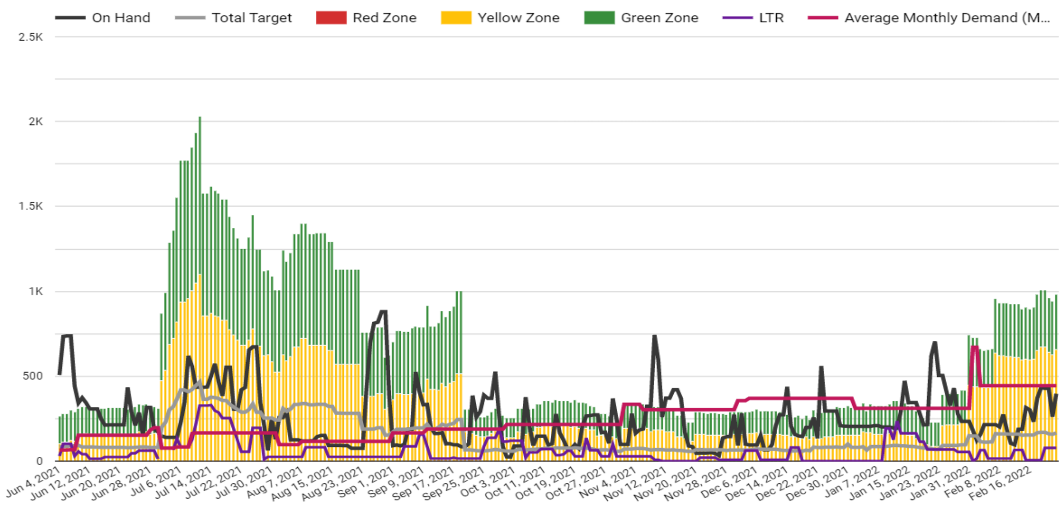


Fig.6.9. *Historical Finished Good Inventory for 859991602220*

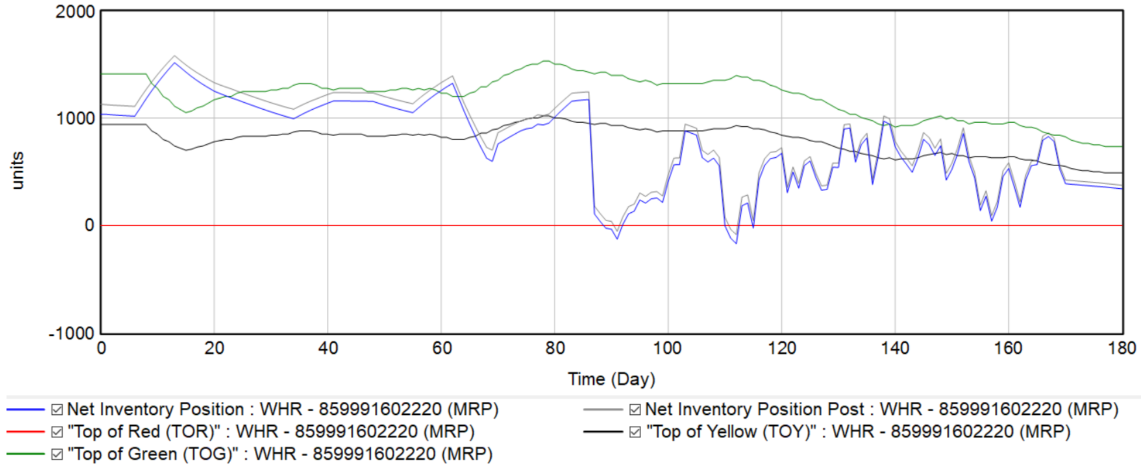
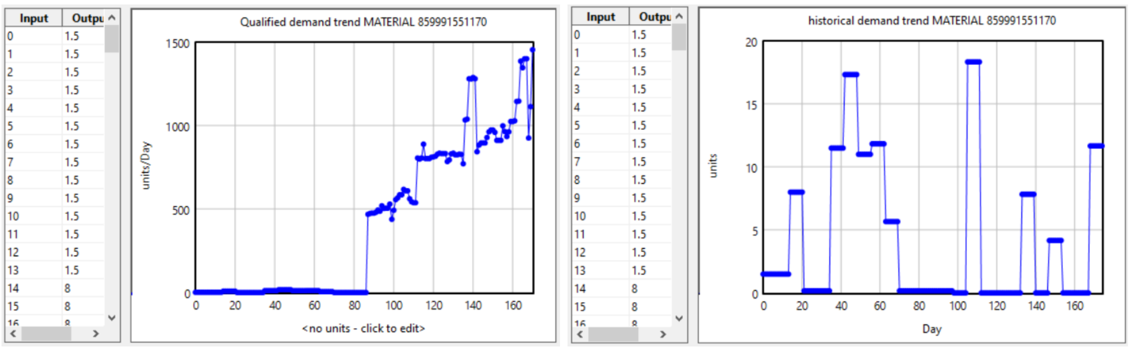


Fig.6.10. *Model Net Inventory Position for 859991602220 under MRP-setting*



MATERIAL	Lead Time	moq	oct	dvf	ltf	red_zone
859991551170	10	9	1	0.8	0.5	0

Fig.6.11. *Input data for 859991551170*

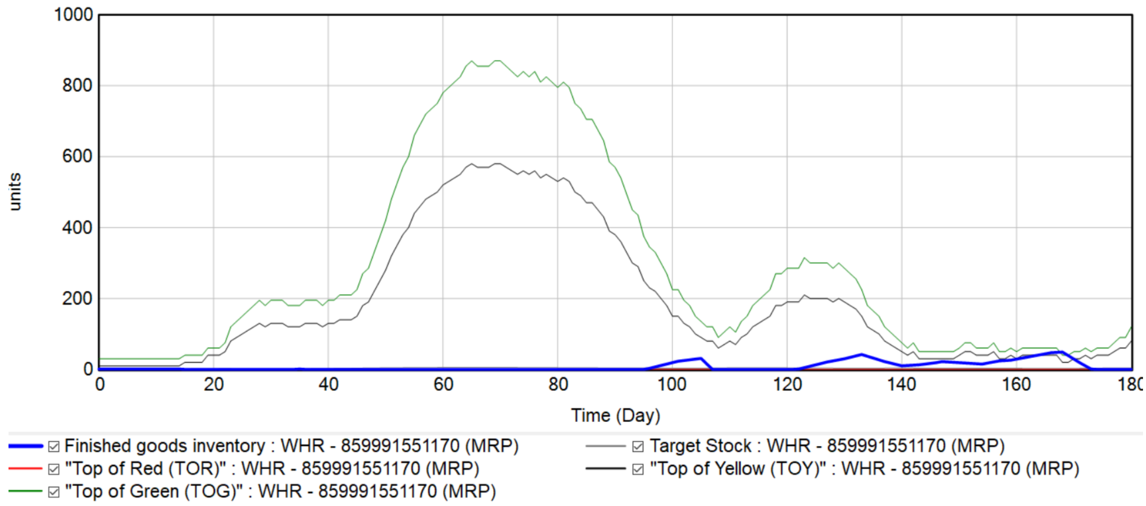


Fig.6.12. *Model Finished Goods Inventory for 859991551170 under MRP-setting*

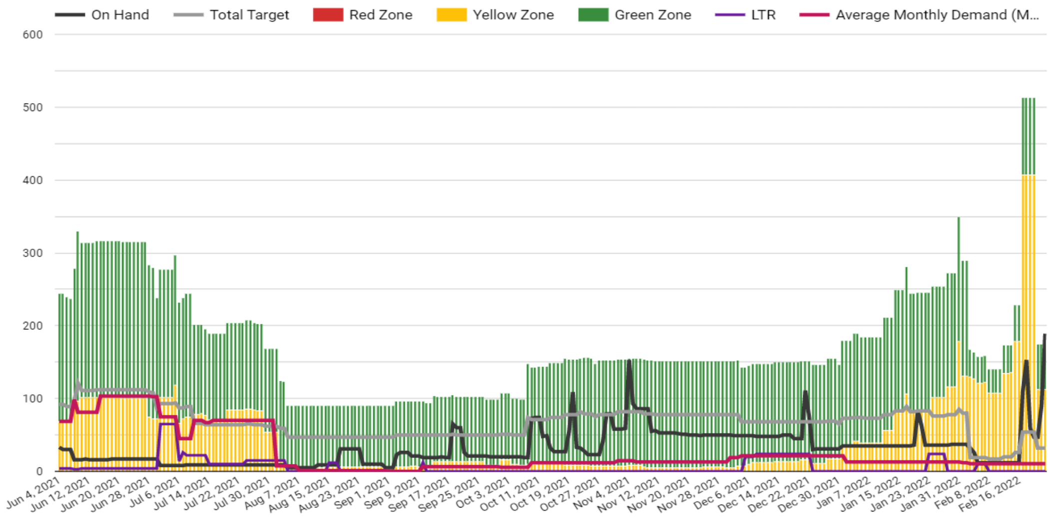


Fig.6.13. *Historical Finished Good Inventory for 859991551170*

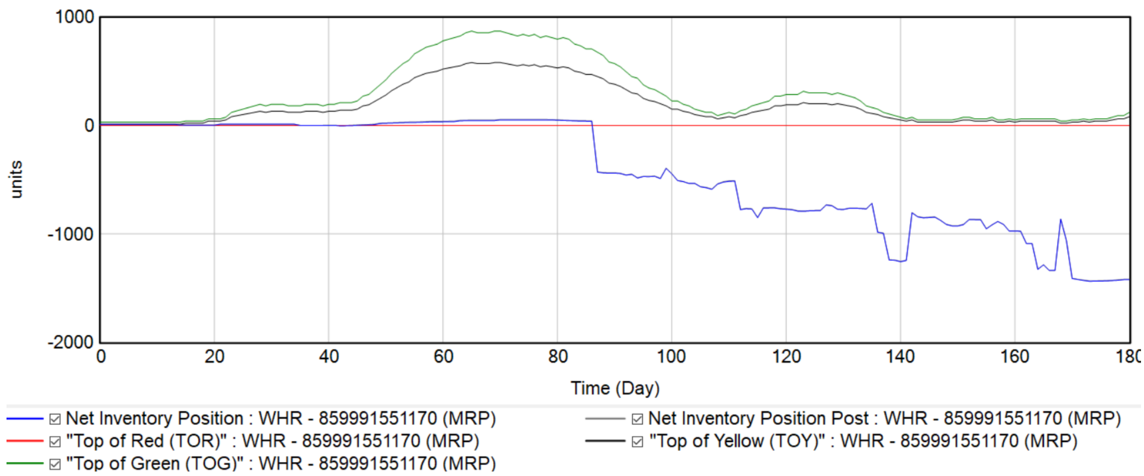
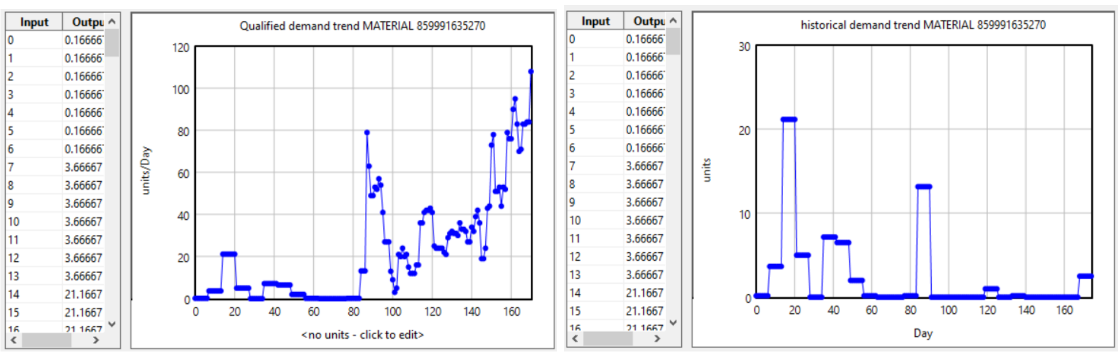


Fig.6.14. *Model Net Flow Position for 859991551170 under MRP-setting*



MATERIAL	Lead Time	moq	oct	dvf	ltf	red_zone
859991635270	10	8	1	0.8	0.5	0

Fig.6.15. *Input data for 859991635270*

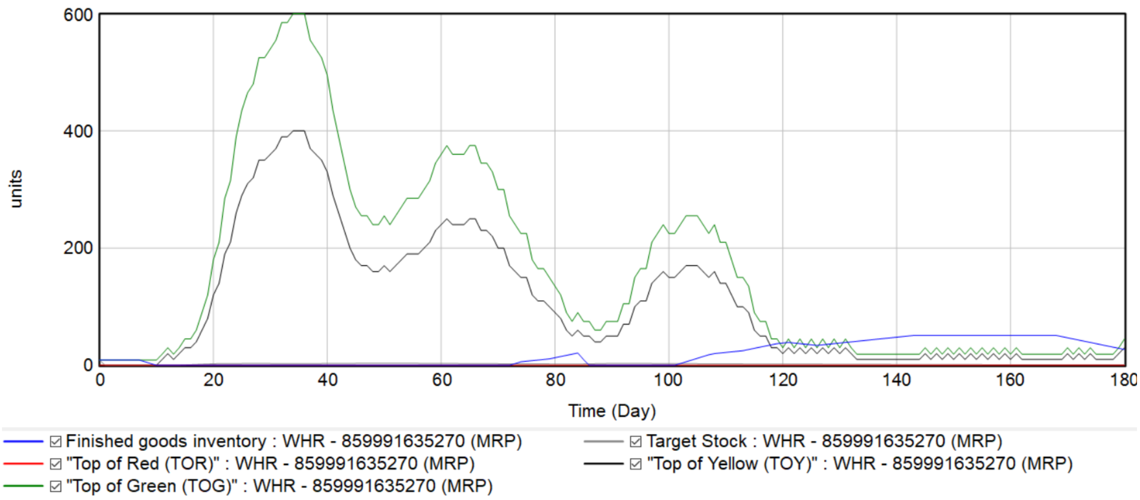


Fig.6.16. *Model Finished Goods Inventory for 859991635270 under MRP-setting*

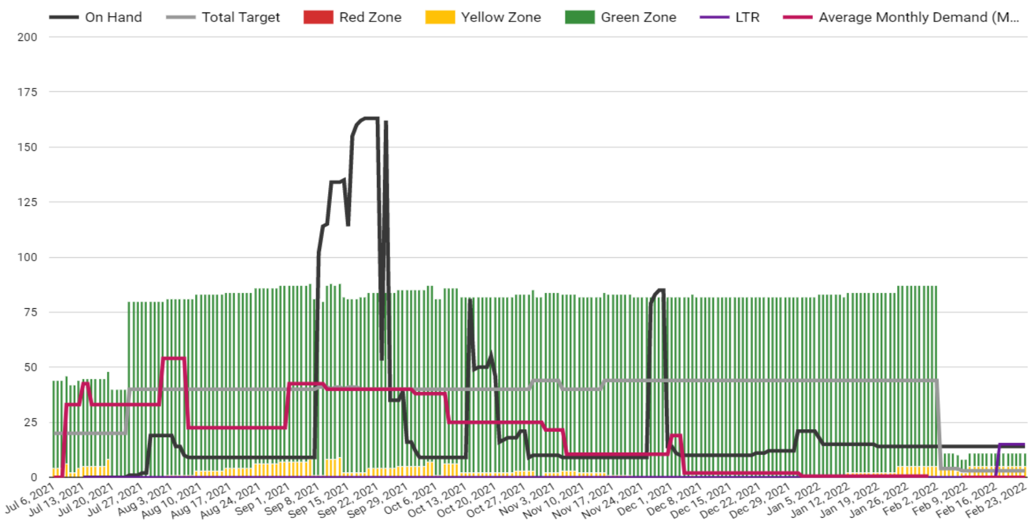


Fig.6.17. *Historical Finished Good Inventory for 859991635270*

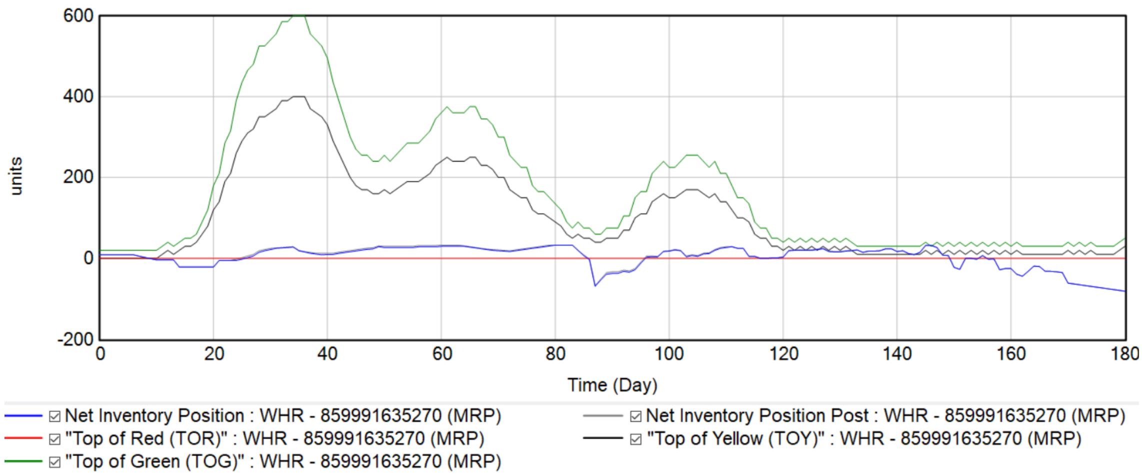


Fig.6.18. *Model Net Flow Position for 859991635270 under MRP-setting*

6.2. Model response to historical data under DDMRP setting

After the dismal results obtained in the previous paragraph, the DDMRP setting was anyway tested in order to have a grasp of how DDMRP would have reacted under the historical demand trend.

Apart for the 859991602220 where the DDMRP behaviour seems as expected, **also the DDMRP results under the Whirlpool data settings seem generally incorrect**, claiming that for 859991551170 and 859991635270 a huge sudden increase in inventory occurs after the decoupled position are stocked-out for a long period of time. While this response makes sense with DDMRP theory, given that when the decoupled position is stocked out then the NFE will always generate a replenishment order since the decouple position integrity is rebuilt. Thus, when stockouts occur, the DDMRP seems to **overreach to the disruption by not fully considering the status of the supply line of new materials on order**. Then, as seen in Sterman, when all issued orders during the stockout arrive, suddenly the decouple position overshoots its target, accumulating excesses, leading to **no more orders since the net flow position is restored within the [TOY, TOG] bounds.**

While those conclusions sound incorrect given the NFE formulation seen in Chap.2, this was the only cause the author could find to explain the model response. On the other hand, in support of such a claim it can be seen that, as seen in Chap.2, when the decoupled position is stocked-out **it completely loses its capability of shielding the productive environment from the Bullwhip effect**. Thus, all variability in the demand signal is passed to the downstream nodes and amplified, leading to overactive behaviours. On the other hand, **such approach to disruption seems to allow DDMRP to better cope with demand variability**, as the Service Level under the BZ and CZ SKU runs produced higher performances than the MRP runs.

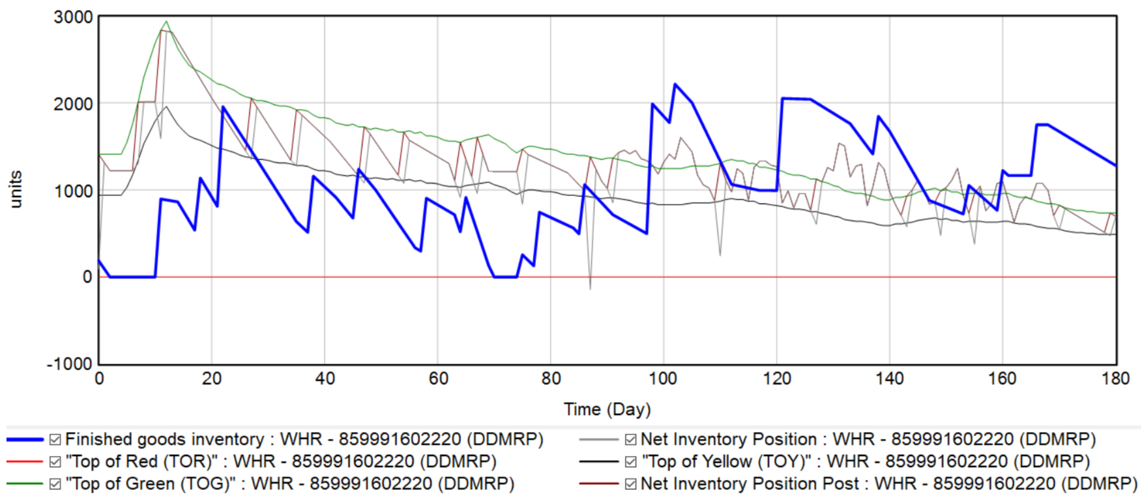


Fig.6.19. *Model Net Flow Position for 859991602220 under MRP-setting*

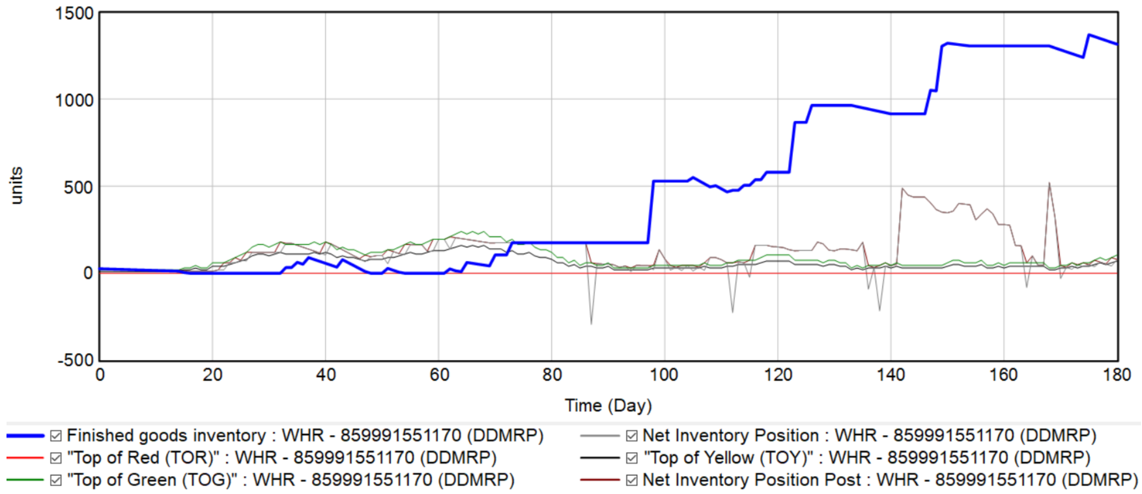


Fig.6.20. *Model Net Flow Position for 859991551170 under MRP-setting*

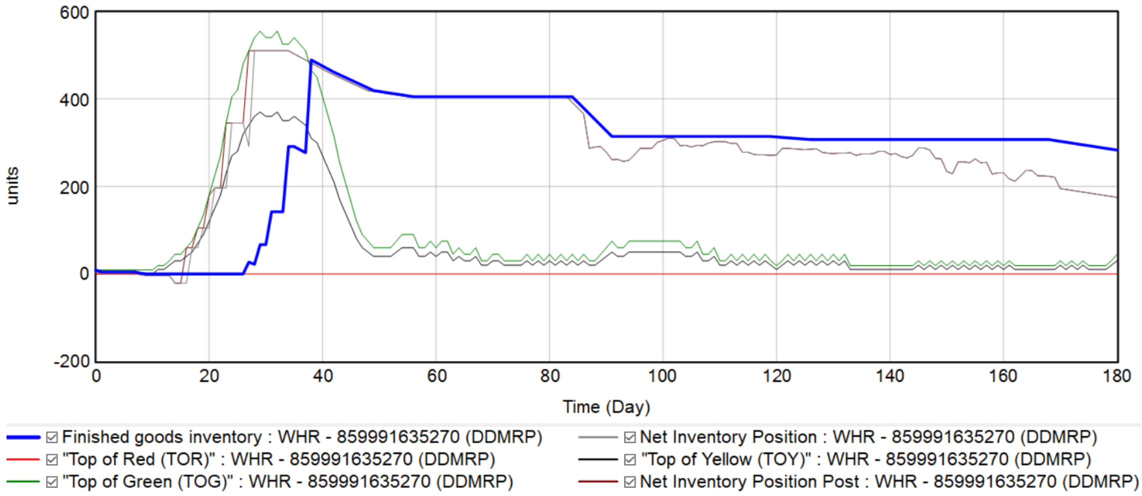


Fig.6.21. *Model Net Flow Position for 859991635270 under DDMRP-setting*

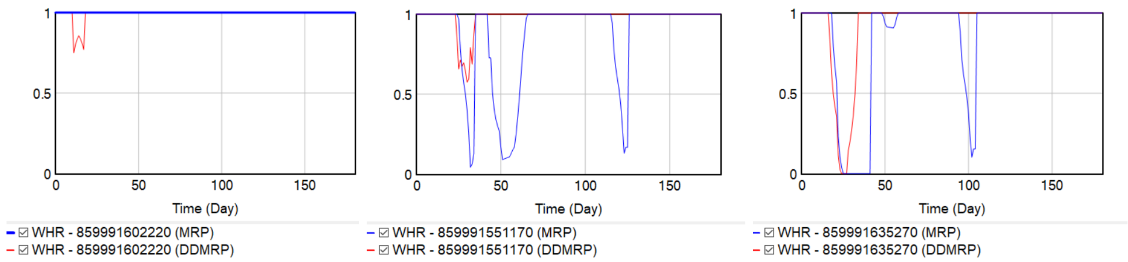


Fig.6.22. *Service Level under for the different SKU runs*

Chapter 7

Conclusions

In this study a deep review of DDMRP has been performed. Because DDMRP, as all other inventory management policies, is rooted in the bigger context of Supply-Chains, such context was reviewed too. It was shown that the basic assumption buried under the MRP-based approach to material management fails to account for the VUCA fabric of the modern supply-chain context, and that nervousness is a consequence of loading a precise "*netting-to-zero*" procedure, such as MRP, with imprecise forecasted data. Proper communication and strategic partnerships along the chain are the way to contrast the propagation of Bullwhip oscillations.

Then, the case study of the Whirlpool EMEA inventory growth during the surge of COVID-19 pandemic in May 2021 and the *DDMRP implementation Cassinetta pilot project* run to fight it, were illustrated. By the opportunity given to the author of participating in such a pilot project during his internship at the company, the current study developed. Upon such experience on the field, this study performed an **empirical analysis of DDMRP performance by exploiting the System Dynamics modelling approach** *to derive whether DDMRP extension to most of the Whirlpool SKUs were to be beneficial for the company and provide a better strategy for inventory*. A SD model made by 6 submodels was developed following the J. Sterman seminal work done regarding supply-chain analysis using SD. On top of his base models, the author customised them in order to add relevant features of the more realistic Whirlpool case study and implemented the DDMRP logic by minimally modifying the Steramn base equations. It is worth mentioning that **the proposed model represents a first-of-a-kind SD model** *to the author's knowledge* **implementing DDMRP**. This represents, to the author, either the model key weakness and key strength, foreseeing large space for improvements.

As seen in Chap.5 and 6, the toughest part of the study applied during model validation. "*All models are wrong, but some are useful*", indeed the proposed model **proved to provide reasonable results when tested against academic datasets** provided by J. Sterman and the Demand Driven Institute, but **completely failed the task of reproposing the Whirlpool historical trends even qualitatively** when the historical demand trends and initial inventory conditions were loaded into it. Because of such dismaling result, *no further analysis could be carried out and no further questions about the business case could be posed*. However, because the model proved its validity under academic datasets, such dismal responses were anyway analysed and, at this point, it is possible to provide an answer to the *Research Questions* of this study initially stated in Chap.3.

RQ1. *How well does the DDMRP perform with respect to traditional inventory continuous (R, Q) policies in terms of Service Level, Inventory Turnover and average WIP inventory for different ABC-XYZ product demand profiles?*

RQ3. *Does the DDMRP order release logic "stress the system" in presence of internal or external capacity constraints?*

RQ4. *Does DDMRP reduce excess generation during periods of high demand variability generated by unforecastable events like global pandemics and sudden global supply shortages?*

From both academic literature and multiple companies who adopted it, DDMRP is claimed to yield overall improved performance in terms of average inventory and WIP. This study **confirms such a result**, after having compared multiple demand trends between an MRP-like setting and the DDMRP one, thus answering **positively to RQ1.**

On the other hand, **this result seems to occur only when an uncapacitaed system is considered**. As shown in Chap.5, when a capacity bottleneck was introduced to constrain the NFE-based replenishment logic, **DDMRP seem to have a tendency to overreach to downstream starvation**, keeping signalling a dangerous situation and releasing ever-increasing downstream orders as long as the integrity of the decoupled position is restored. Such a behaviour **produces a sudden spike in finished goods inventory levels** when all continuously released orders arrive, thus **producing higher inventory levels and WIP utilisation than MRP**. This result goes in accordance with some of the studies found in literature (Al-Ammar, 2018) where it is claimed the *existence of a domain of applicability of DDMRP on some specific types of SKUs*. However, in this study the characteristics of such an applicability domain were not found.

RQ2. *How sensible are the DDMRP performances to the arbitrarily set LFT and DVF parameters?*

From the sensitivity analysis run at Chap.5, **the impact of LTF and DVF seems to be sensibly high**, presenting high variability of the Finished Goods Inventory levels with the increase of the z-eq factor = LTF(1+DVF). Such results seem to confirm the result found by C. J. Lee about the too loose bounds of the DDMRP SS setting rule, **but the too simplistic analysis run in this study can only suggest such a claim and a more rigorous study would be required.**

RQ5. *How much does the Order Spike Visibility feature of DDMRP drive final performances?*

This study **did not properly answer this research question**.

RQ6. *Is System Dynamics flexible enough to be embedded in current S&OP processes?*

Even if it required to build a model that might be considered slightly complex, **SD adoption in such an operative context like the one of Inventory Management resulted extremely versatile,** allowing to build a model able to compare side-by-side two different inventory management policies. Moreover, once a model of the operative context is built, it can be plugged into a bigger model more strategically oriented, bridging the two environments and letting them feed each other dynamically. It is worth noticing that **these are the aims of the Demand Driven Institute is trying to achieve with its DDMRP**. IAs seen in Chap.2, DDMRP is only the operative module of a bigger S&OP strategic module called *Demand Driven Adaptive Enterprise* (DDAE) *model.*

7.1. Current issues and future steps

Considering all the above,

1. The more stringent priority lies in **understanding why the model responses were so highly inaccurate when loaded with historical data**. Part of such investigation is already performed in Chap.5, where a possible issue with the quality of data retrieved emerged. Because the model proved its validity when loaded with exact input data of well known datasets, the first logical attempt to improve its response is to validate with high confidence the accuracy of data retrieved. To achieve this goal, **sharing the model to the Whirlpool GSS analyst** by highlighting both its strengths and flaws, **is of key importance**;

2. Because DDMRP proved extremely sensible to the arbitrarily set DVF and LTF, a deeper investigation of the insight might be planned by loading the model with the J. Lee, et al, proposed formulation that claims a shrinkage of the DDMRP Safety Stock variability range;

3. As rilevated by DDMRP authors, the effect of very large MOQs on DDMRP performances is not clearly stated. In their studies they obtain that an increase of MOQ did not play favourably to DDMRP. A possible investigation about the issue might be pursued by exploiting the proposed SD model.

4. Finally, the issue found more relevant by the author to advance the DDMRP body-of-knowledge is the one related to **determining whether DDMRP should be generally applied to all environments or whether it should be limited to only some kind of SKUs**. The obtained results about DDMRP overactive behaviours in presence of a capacitated system suggest the latter. From what is seen in Chap.3, *there are no such things as uncapacitated systems.*

Acknowledgements

The author wants to thank the Whirlpool Sourcing Excellence Team, Global Supply Chain Team and Global Information System Team members that gave support throughout these months and made it possible to carry out this study. A special thanks goes to Matteo Coppola, Laura Beatrice Brukarz and Daniel Tinoco Valencia firstly to have allowed the author to participate in the Demand Driven DDP program, a huge commitment being the author just interning in the company at the time. The program gave the author direct access to DDMRP lectured by its creators. During the internship experience they introduced and explained the author into the little details of the frenetic world of supply-chains and procurement, and, more importantly they shared their *ideas*, *trust*, *knowledge*, *passion* and support *endlessly*. This was not taken for granted.

References

1. Achergui A., Allaoui H., Hsu T., "*Strategic DDMRP's Buffer Positioning for hybrid MTO/MTS manufacturing";*
2. Anthes G. H., *"Supply Chain Whirl"*, Computer World;
3. Azzamouri, "*DDMRP: A systematic review and classification"*;
4. A.P.I.C.S., *"Operations Management Body of Knowledge Framework", Third Edition;*
5. Bahu B., Bironneau L., Hovelaque V.(2019): "*Compréhension du DDMRP et de son adoption : premiers éléments empiriques"*, Logistique & Management, DOI: 10.1080/12507970.2018.1547130;
6. Balderstone S.J., Mabin V.J., *"A Review of Goldratt's Theory of Constraints (TOC): Lessons from the international literature";*
7. Cagliano A.C., Carlin A., Mangano G., Rafele C., "*Analyzing the diffusion of eco-friendly vans for urban freight distribution"*;
8. Carlin A., "*I costi logistici"*, Course Slides;
9. Chang W.S., Lin Y.T., "*The effect of lead-time on supply chain resilience performance";*
10. Clark C.E., "*Mathematical Analysis of an Inventory Case"*, https://doi.org/10.1287/opre.5.5.627
11. Daskin M. S., Coullard C. R., Shen Z. M., *"An Inventory-Location Model: Formulation, Solution Algorithm and Computational Results";*
12. De Marco, Cagliano A.C., Rafele C., *"Forecasting the Diffusion of a Mobile Service for Freight Distribution";*
13. Demir L., Tunali S.. Eliiyi D.T., *"The state of the art on buffer allocation problem: a comprehensive survey";*
14. Dessevre G., Lamothe J., Martin G., Pellerin G., Baptiste P., Lauras M., "*Decoupled Lead Time in finite capacity flowshop: a feedback loop approach";*
15. Deloitte, "*Making the case for inventory optimization"*,2019 https://www2.deloitte.com/content/dam/Deloitte/us/Documents/process-and-operations/us-inventory-management.pdf;
16. Demand Driven Institute, "*Demand Driven Planner Program, Course Slides",Third Ed..;*
17. DemandDrivenTechnologies, "*Adapting To Supply Chain Disruption",* white-paper;

18. DemandDrivenTehcnologies, “*Simulating DDMRP Buffers at 2014 APICS conference”*;
19. Dominguez R., Cannella S., Ponte B., Framinan J. M., *“Information sharing in decentralised supply chains with partial collaboration”;*
20. Erlebacher S. J., Meller R. D*., “The interaction of location and inventory in designing distribution systems”;*
21. Erraoui, “*Demand Driven DRP-Assessment of a new approach to distribution”;*
22. Mangano G., Zenezini G., Cagliano A.C., De Marco A*., “The dynamics of diffusion of an electronic platform supporting City Logistics services”;*
23. Goldratt E.M., *“Critical Chain. A Business Novel”;*
24. Grant R*., “Contemporary Strategy Analysis”, 9th Ed;*
25. Grubbstrom R. W, “*A stochastic model of multi-level-multi-stage capacity-constrained production-inventory system”;*
26. Gupta M*., “Comparing TOC with MRP and JIT. A literature review”;*
27. Gupta M.C., Boyd L.H., *“Theory of constraints: a theory for operations management”;*
28. Ihme M., Stratton R., “*Evaluating Demand Driven MRP: a case based simulated study”;*
29. Janamanchi B., “*Reducing bullwhip oscillation in a supply chain: a system dynamics model-based study”;*
30. Javid A., Azad N., *“Incorporating location, routing and inventory decisions in supply chain network design”*
31. Jiang J., Rim S.C., “*Strategic Inventory Positioning in BOM with Multiple Parents Using ASR Lead Time”;*
32. Kortabarria A., Apaolaza U., Lizarralde A., Itxaso A., “*Material management without forecasting: From MRP to demand driven MRP”,* Journal of Industrial Engineering and Management, 11(4), 632-650. https://doi.org/10.3926/jiem.2654;
33. Kruger J.,Dunning D, “*Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments”;*
34. Kumar S., “*Has MRP run its course?A review of contemporary developments in planning systems”;*
35. Langroodi R.R.P., Amiri M., “*A system dynamics modelling approach for a multi-level, multi-product, multi-region supply chain under demand uncertainty”;*
36. Lee C.J., S.K. Rim, “*A Mathematical Safety Stock Model for DDMRP Inventory Replenishment”;*
37. Li H., Pedrielli G., Lee L.H., Chew E. P., *“Enhancement of supply chain resilience through inter-echelon information sharing”;*
38. Lizarralde-Aiastui A., Apaolaza-Perez de Eulate U., Mediavilla-Guisasola, M. (2020). “*A Strategic Approach for Bottleneck Identification in Make-To-Order Environments: A Drum-Buffer-Rope Action Research Based Case Study”,* Journal of Industrial Engineering and Management, 13(1), 18-37. https://doi.org/10.3926/jiem.2868;
39. Lummus R., Vokurka R.J., “*Defining supply chain management”,* Industrial Management & Data Systems*;*
40. Miclo R., Fontanili F. Lauras M., Lamothe, J.Milian B.., “*MRP vs. Demand-Driven MRP: Towards an Objective Comparison, 2015;*
41. Miclo R.Fontanili, F., Lauras M., Lamothe J. Milian B., “*An empirical comparison of MRPII and DDMRP”,* 2016. International Federation of Automatic Control;
42. Miclo R., M. Lauras, F. Fontanili, J. Lamothe, S. A. Melnyk (2018): “*Demand Driven MRP: assessment of a new approach to materials management”,* International Journal of Production Research, DOI: 10.1080/00207543.2018.1464230;

43. Orue, A, Lizarralde, A., Kortabarria, A., "*DDMRP: The need to standardize an implementation process",* International Journal of Production Management and Engineering*, 2019*;
44. Park S., Lee T. E., Sung C. S., *"A three-level supply chain network design model with risk-pooling and lead times";*
45. Pekarˇc ́ıkov ́a M., Trebuˇna P., Kliment M., Trojan J., "*Demand Driven Material RequirementsPlanning. Some Methodological and Practical Comments";*
46. Perugini A., Cagliano A.C., *"Applicazione di System Dynamics per l'analisi della logistica interna: Il caso Loccioni";*
47. Porter M., "*Competitive Advantage Creating and Sustaining Superior Performance";*
48. Porter M.*, "Competitive Strategy Techniques for Analyzing Industries and Competitors";*
49. Porter M., "*The Five Competitive Forces That Shape Strategy";*
50. Ptak C., Smith C., "*Demand Driven Material Requirements Planning (DDMRP)",* Third Ed.*;*
51. Rafele C., Carlin A., Delleani B., "*Supply Chain Management*", Course Slides, 2020.;
52. Schlösser T., Dunning D., Johnson K. L., Kruger J., "*How unaware are the unskilled? Empirical tests of the "signal extraction" counter explanation for the Dunning–Kruger effect in self-evaluation of performance"*;
53. Shofa M. J., Widyarto W. O.*, "Effective Production Control in an Automotive Industry: MRP vs. Demand-Driven MRP";*
54. Shofa M.J., Moeis A. O., Restiana N., *"Effective production planning for purchased part under long lead time and uncertain demand: MRP Vs demand-driven MRP";*
55. Simchi-Levi D.*, "Designing and Managing the Supply Chain",* Chap. 1, 2,5,6, 14;
56. Simsir F., Ekmekci D., "*A metaheuristic solution approach to capacitated vehicle routing and network optimization";*
57. Sterman J. D.*, "Business Dynamics Systems Thinking and Modeling for a Complex World",* Chap.1-16;
58. Stevenson M., Hendry L. C., Kingsman B. G. (2005) *"A review of production planning and control: the applicability of key concepts to the make-to-order industry",* International Journal of Production Research, 43:5, 869-898, DOI: 10.1080/0020754042000298520;
59. Tako A., Robinson S., "*The application of discrete event simulation and system dynamics in the logistics and supply chain context";*
60. Thürer M., Fernandes N. O., Stevenson M.: *"Production planning and control in multi-stage assembly systems: an assessment of Kanban, MRP, OPT (DBR) and DDMRP by simulation",* International Journal of Production Research, DOI: 10.1080/00207543.2020.1849847;
61. Velasco Acosta A.P., Mascle C., Baptiste P. (2019): "*Applicability of Demand-Driven MRP in a complex manufacturing environment"*, International Journal of Production Research, DOI: 10.1080/00207543.2019.1650978;
62. Wang J., Zhou Y., Wang Y., J. Zhang, Chen C. L. P., Zheng Z., "*Multiobjective Vehicle Routing Problems With Simultaneous Delivery and Pickup and Time Windows: Formulation, Instances, and Algorithm";*
63. Whirlpool, "*Whirlpool Global Manufacturing*", 2020, http://assets.whirlpoolcorp.com/files/2020_Whirlpool-Global-Manufacturing.pdf
64. DemandDrivenTechnologies, "*Adapting To Supply Chain Disruption*", 2020;
65. Harvard Business School, "Change at Whirlpool Corp. (A)", 2005, https://hbsp.harvard.edu/search?N=&Nrpp=25&Ntt=whirlpool&searchLocation=header;
66. New York Times, "How the World Run Out of everything", 2021, https://www.nytimes.com/2021/06/01/business/coronavirus-global-shortages.html;

67. PwC, “Demand Driven MRP”, 2020, *https://www.pwc.com/it/en/services/consulting/operations/ddmrp.html*;
68. Whirlpool, “*Modello di Organizzazione e Gestione*“, 2018, https://www.whirlpool.eu/pdf/MOG_231_WHIRLPOOL_EMEA_per_sito.pdf;
69. Whirlpool, “*Supplier Code of Conduct”*, 2021, https://www.whirlpoolcorp.com/supplier-code-of-conduct/;
70. Whirlpool, “*Wroclaw and Cassinetta sites conduct the first World Class Manufacturing audit*”, 2017, Wroclaw and Cassinetta sites conduct the first World Class Manufacturing audit | Whirlpool Corporati

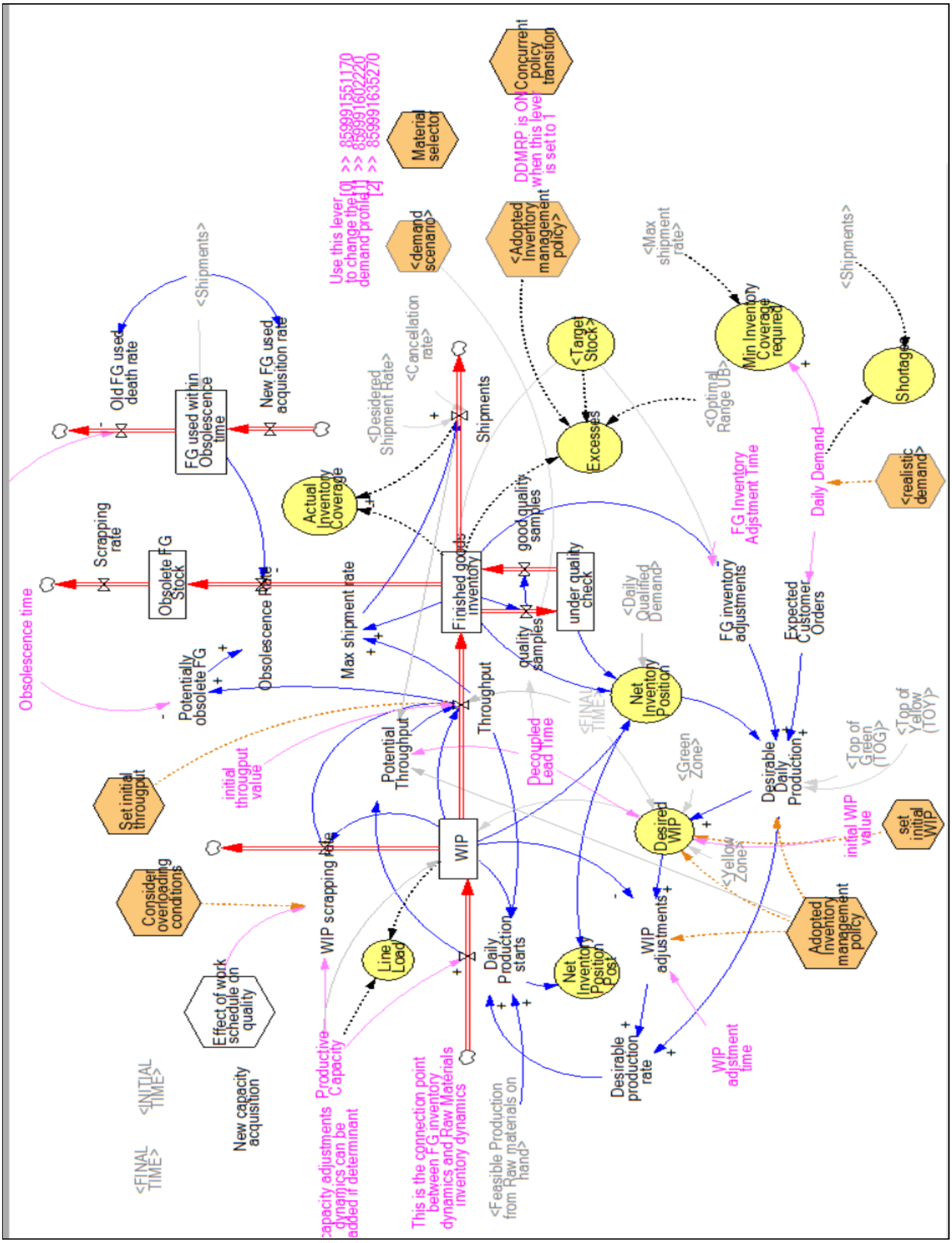
Appendix

10.1. Interface Python Script interface script between the DP and Vensim

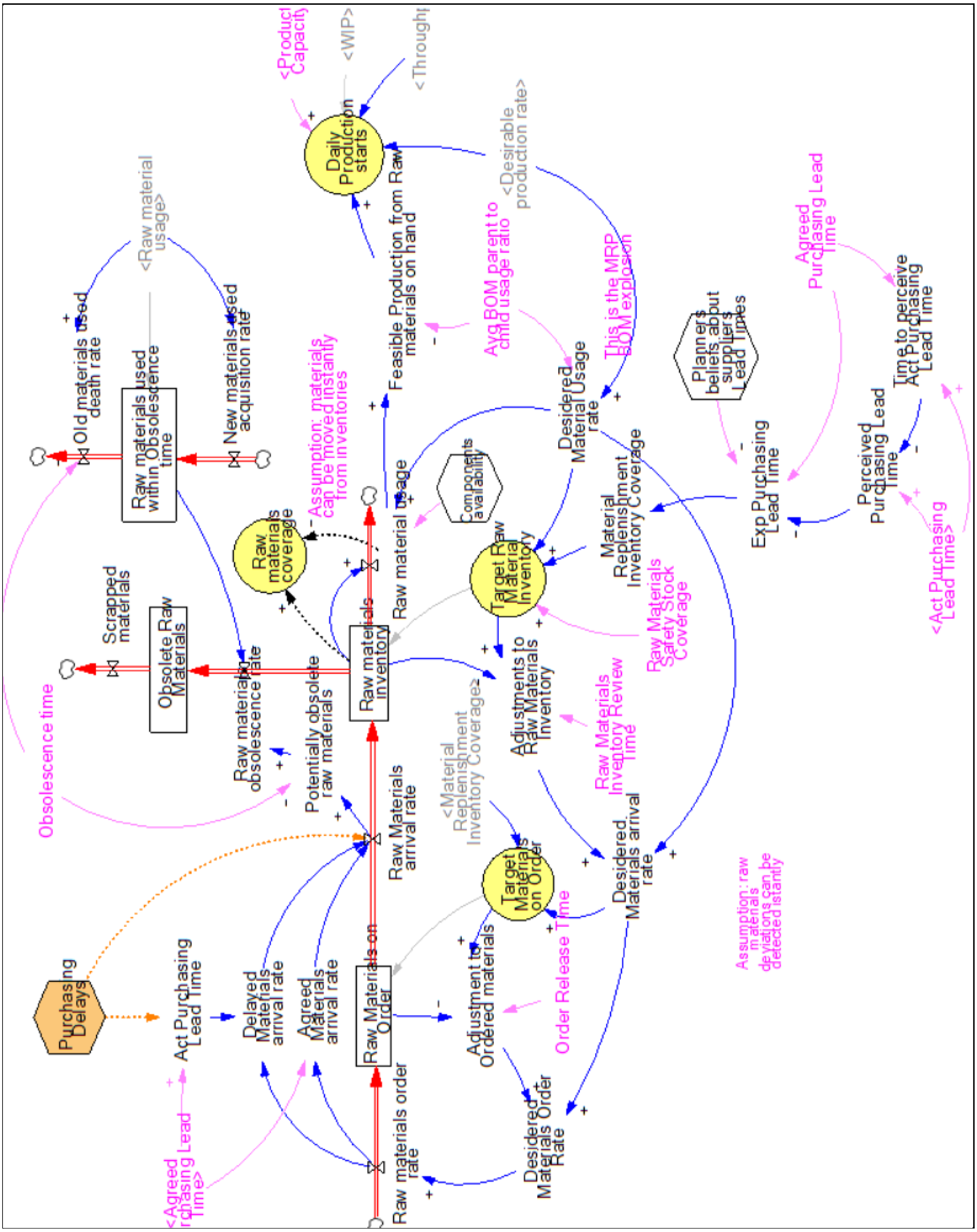
```python
def build_vensim_lookup_from_csv(file_uri: str, destination_file_name: str):
    """
        Given a .CSV file containing 2 columns [MATERIALCODE, RELATIVE-TIMESTAMP, QUANTITY] assumed
        to be ascendly ordered by Relative Timestamps it outputs to the console the the properly
        formatted string that produces an equivalent vensim lookup function if copy-pasted in it.

        [IMPORTANT]
        Missing values for any timestamp between min and max are imposed to be = 0 to avoid any
        linear interpolation done in Vensim later.
     """
     if '"' in file_uri:
        file_uri = file_uri[1:-1]
    vns_lookup: str = "[(0,0)-(10,10)]"
    with open(rf"{file_uri}", "r") as f:
        data: list = [
          (int(l.split(",")[1].strip("\n")),
          float(l.split(",")[2].strip("\n"))) for i, l in enumerate(f) if i != 0
          ]
        vns_lookup = [(i,0) for i in range(len(data))]
        for d in data:
            if d[0]>=0:
                vns_lookup[d[0]]=d
        vns_lookup.insert(0,"[(0,0)-(10,10)]")
        data = vns_lookup[0]
        for i in range(1, len(vns_lookup)):
            data += f",\n{vns_lookup[i]}"
        if destination_file_name == "":
            print(data)
        else:
        with open(path.join(path.join(environ['USERPROFILE']),
                  'Desktop\\', destination_file_name+".txt"), "w") as f:
             f.write(data)
        with open(path.join(path.join(environ['USERPROFILE']),
                  'Desktop\\demand-trend-all-steps.csv'), "w") as f:
            for i, d in enumerate(vns_lookup):
                if i==0:
                    f.write(f"CODE,REL-TIMESTAMP,DEMAND\n")
                else
                    f.write(f"XXXXXXX,{d[0]},{d[1]}\n")
```

10.2 Final System Dynamics Model

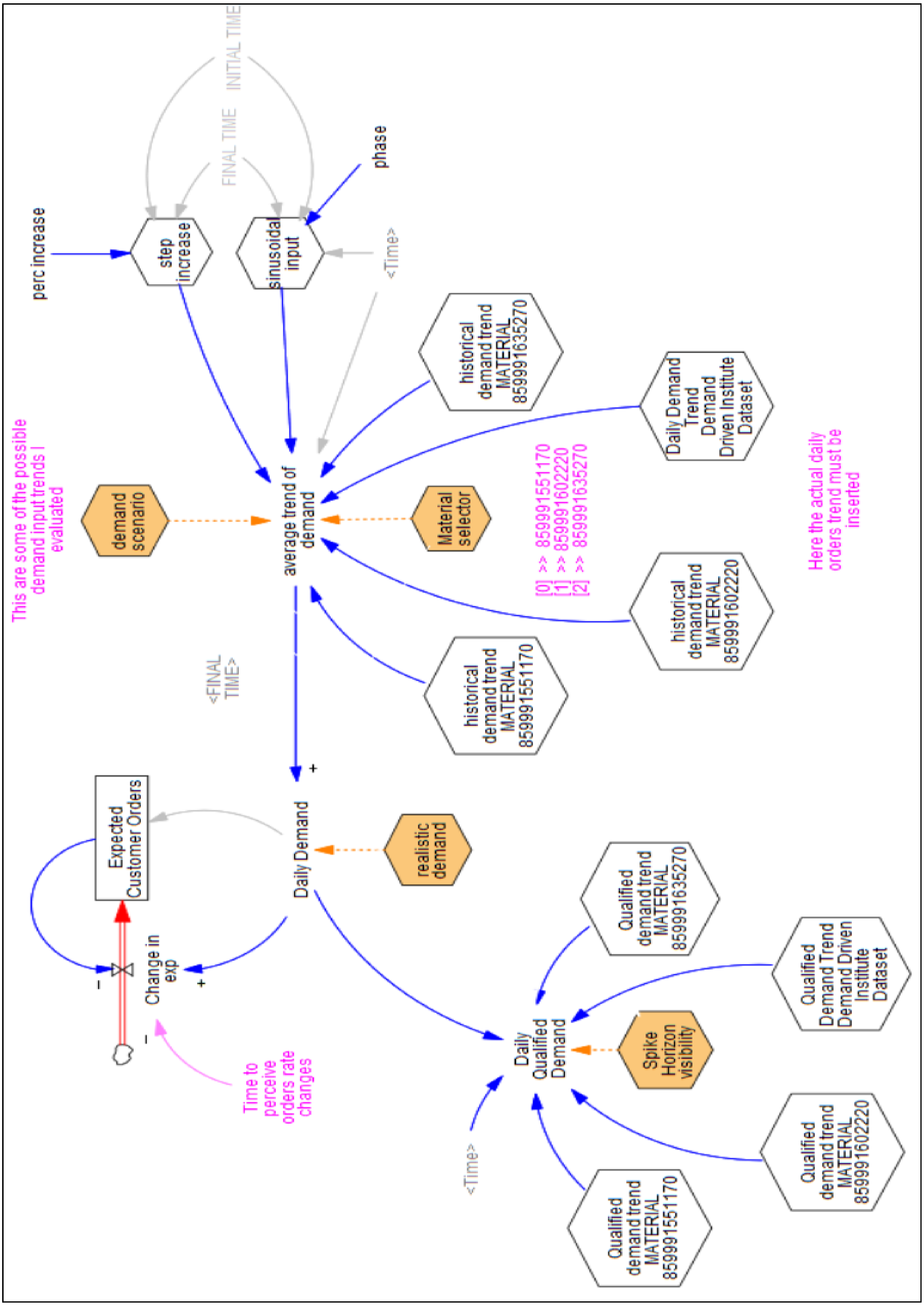
Finished Good Inventory Module



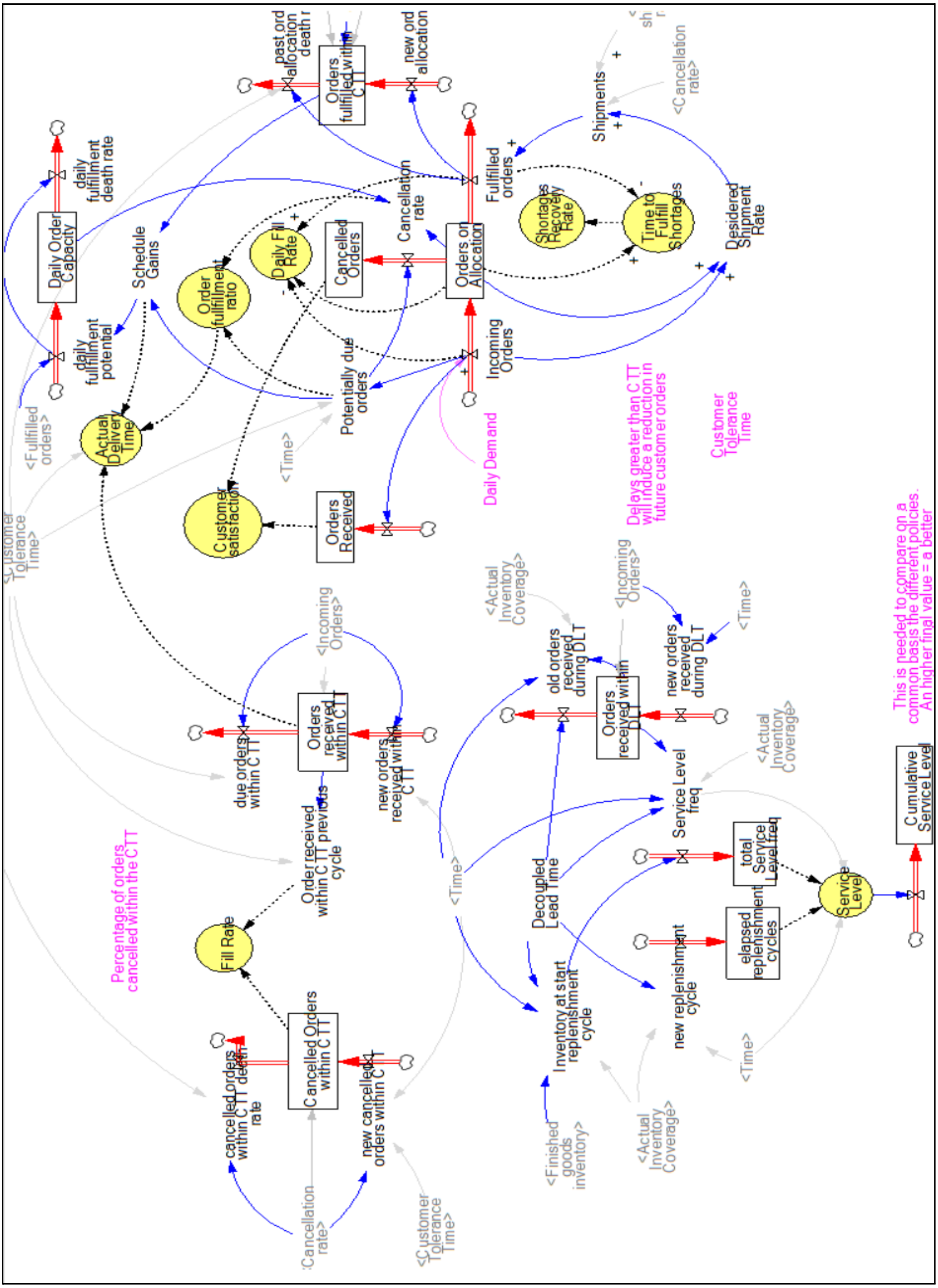
Raw Materials Inventory Module



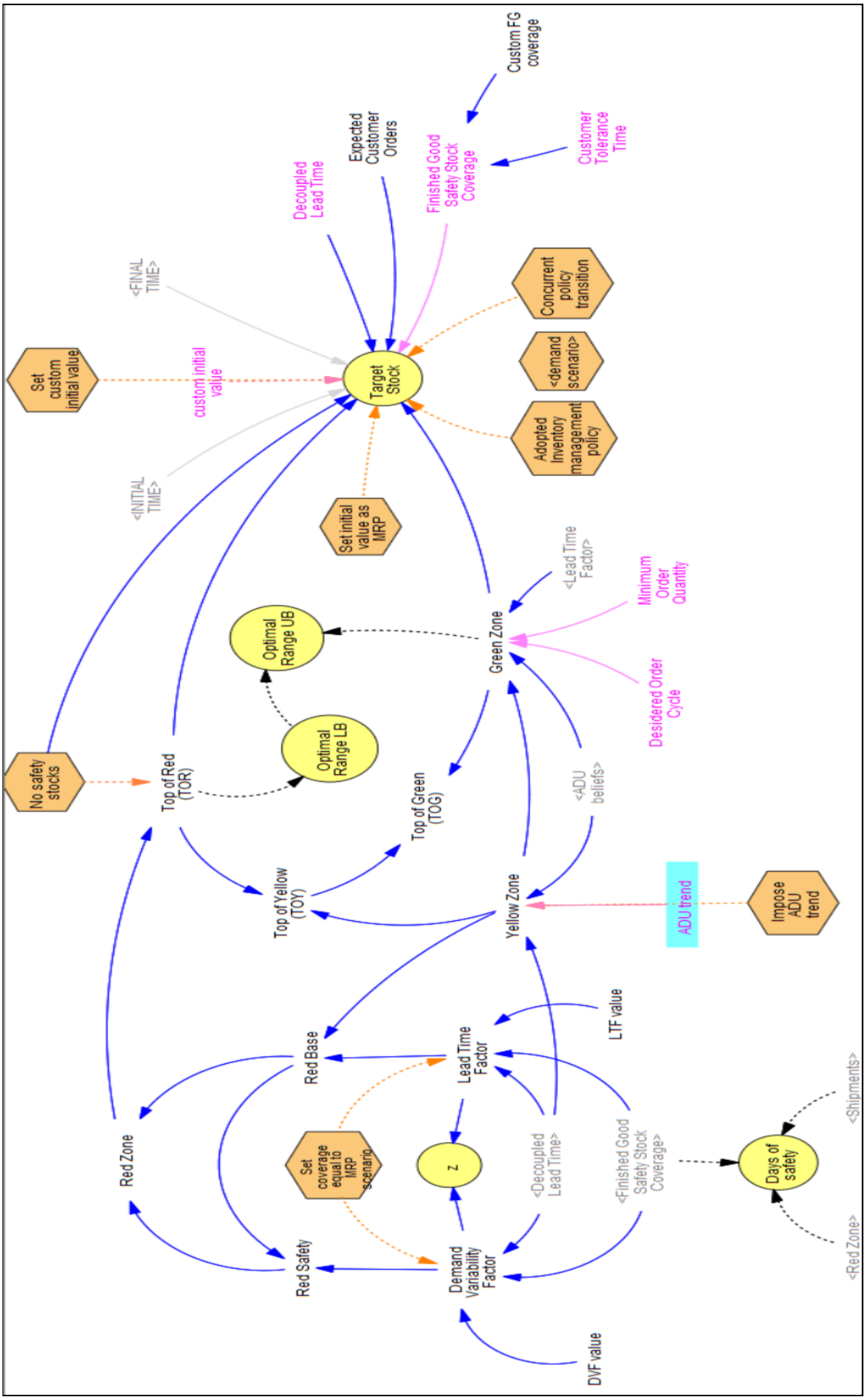
Demand Forecasting Module



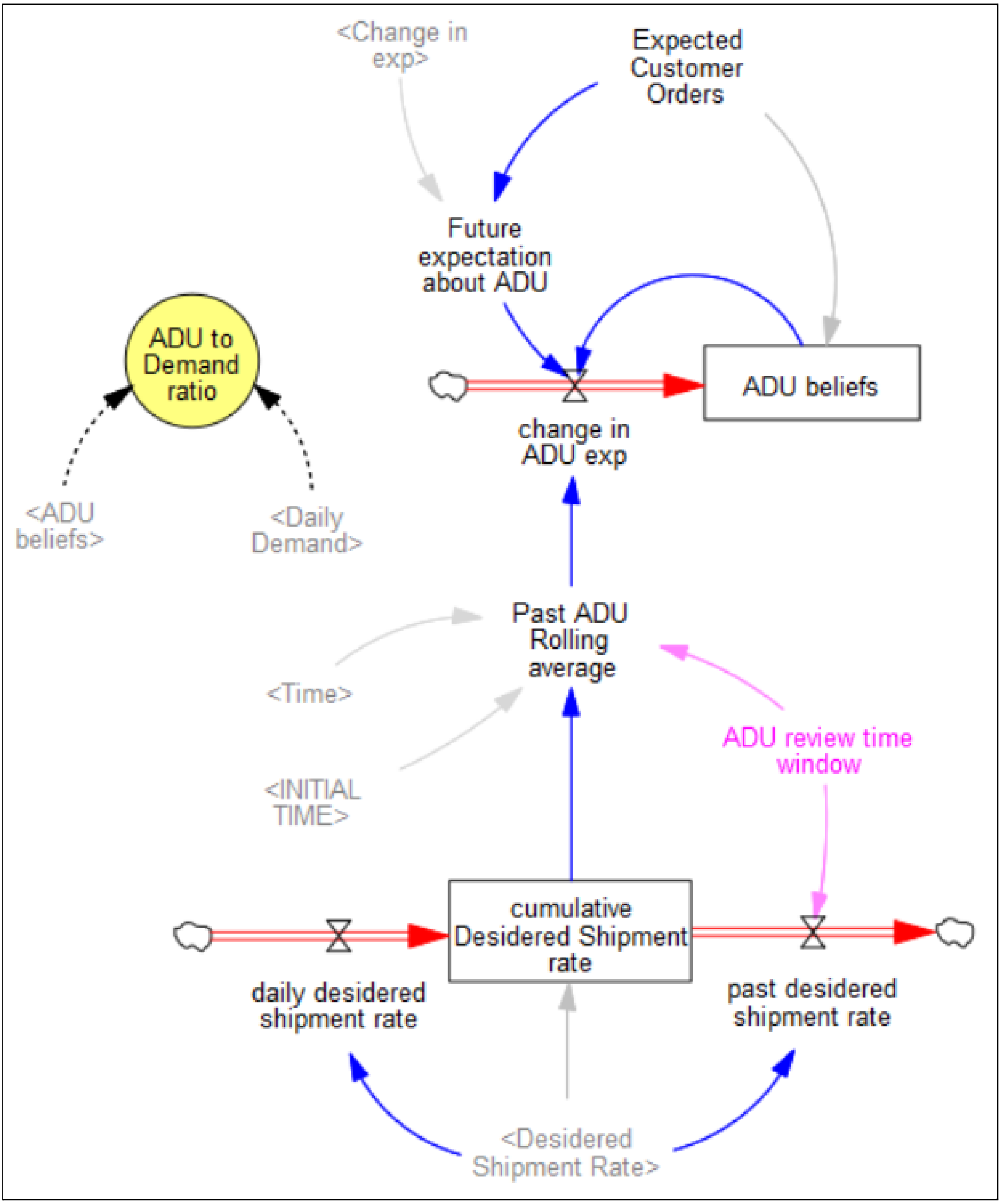
Order Fulfilment Module



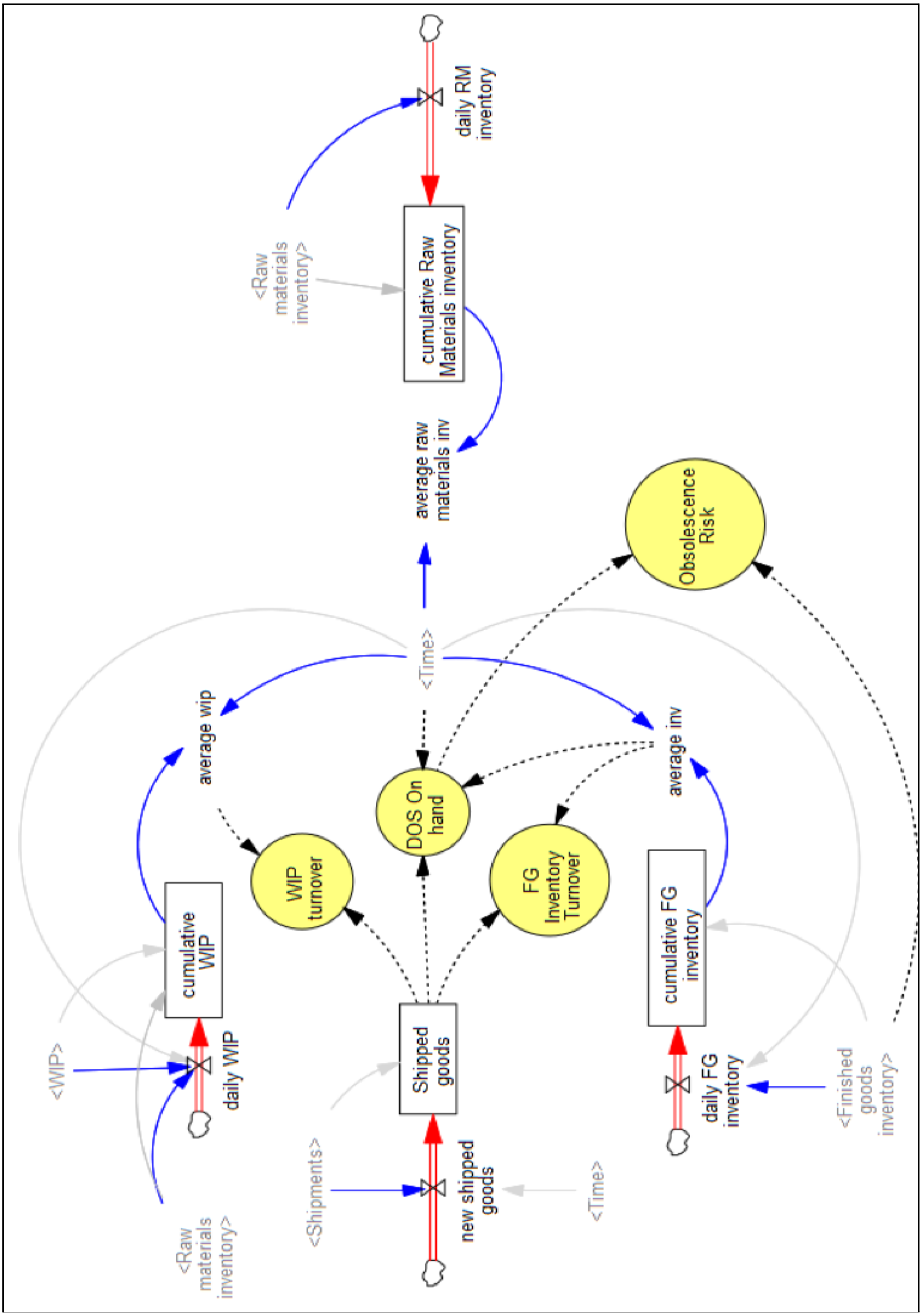
S&OP Module


Custom FG coverage
Expected Customer Orders
Decoupled Lead Time
Finished Good Safety Stock Coverage
Customer Tolerance Time
<FINAL TIME>
Set custom initial value
custom initial value
Target Stock
Concurrent policy transition
<demand scenario>
Adopted Inventory management policy
<INITIAL TIME>
Set initial value as MRP
<Lead Time Factor>
Minimum Order Quantity
Optimal Range UB
Green Zone
Desidered Order Cycle
Optimal Range LB
No safety stocks
Top of Red (TOR)
Top of Green (TOG)
<ADU beliefs>
ADU trend
Impose ADU trend
Top of Yellow (TOY)
Yellow Zone
Red Base
Lead Time Factor
LTF value
Red Zone
Set coverage equal to MRP scenario
z
<Decoupled Lead Time>
<Finished Good Safety Stock Coverage>
Days of safety
<Shipments>
<Red Zone>
Red Safety
Demand Variability Factor
DVF value

ADU Estimation Module



Financials Module



A.1: The data-retrieval SQL-procedure

```
-- the procedure pulls all the data required for running the SD DDMRP model given 2 start and end dates

-- the procedure also provides the model initial conditions -> values for rel_timestamp = 0
```

```
BEGIN
  DECLARE dt_sim_start DATE;
  DECLARE dt_sim_end DATE;
  DECLARE target_sku_code STRING;
  DECLARE aggreagate_plants BOOLEAN;

    SET target_sku_code = "859991602220";
    SET aggreagate_plants = TRUE;
    SET dt_sim_start = DATE("2021-01-01");
    SET dt_sim_end = DATE("2023-01-01");


    SET dt_sim_end = DATE_ADD(DATE_TRUNC(dt_sim_end, WEEK), INTERVAL 7 DAY);

    IF aggreagate_plants THEN

        SELECT
            *
        FROM
            (
               -- the following aggregates all cassinetta plants quantities together and generates daily demand trend
             -- from weekly ones assuming equal workload allocation during 6 days week
                with wk_dmd_crv as
                (
                    SELECT
                        material,
                        ref_week,
                        sum(demand_total_qty) value,
                    FROM `ind-inv-fg.demand`
                    where
                        ref_week BETWEEN dt_sim_start AND dt_sim_end
                        AND plant in ("C020", "C021","C022")
                        AND material = target_sku_code
                    group by 1, 2
                ),
                dt_sim as
                (
                    select
                        material,
                        MIN(ref_week) ini,
                        DATE_ADD(MAX(ref_week), INTERVAL 6 DAY) lst
                    from
                        wk_dmd_crv
                    group by 1
                ),
                dd_dmd_crv as
                (
                    with dd_cal as
                    (
                        select
                            dt_sim.material,
                            l as d_date
                        FROM
                            dt_sim, UNNEST(GENERATE_DATE_ARRAY(dt_sim.ini, dt_sim.lst)) l
                    )

                    select
                        material,
                        d_date,
                        YEAR,
                        ISOWEEK,
                            (
```

```
         LAST_VALUE(value IGNORE NULLS)
         OVER (PARTITION BY material, YEAR, ISOWEEK ORDER BY d_date)
        )/6 as value
    from
    (
        select
            s.material,
            s.d_date,
            EXTRACT(YEAR FROM s.d_date) YEAR,
            EXTRACT(ISOWEEK FROM s.d_date) ISOWEEK,
            d.value
        from dd_cal s
        left join wk_dmd_crv d
        on s.material=d.material AND s.d_date=d.ref_week
    )
),
dd_hist_trends_qual_dmd_nfp as
(
-- REVERSE ENGINEERED APPROACH TO EXTRACT NFE HISTORY BY MATERIAL PLANT
    -- this gives the historical qualified demand trend input  and the net flow position
    SELECT
        material,
        creation_date,
        cod_argument,
        value
    FROM
        (
            SELECT
                s.material,
                s.creation_date,
                SUM(d.qual_ord_qty) daily_qual_demand,
                SUM(d.nfe_qty) daily_net_flow_pos,
    FROM `ind-inv-fg.target_stock_history` s
            LEFT JOIN
            (
                SELECT
                    d.market,
                    s.material,
                    s.creation_date,
                    s.qual_ord_qty,
                    s.nfe_qty
                FROM `ind-inv-fg.nfe_by_mat_sales_area` s
                LEFT JOIN
                (
                    SELECT
                    DISTINCT
                        sales_area,
                        market
                    FROM `ind-inv-fg.external_data.market_to_sales_area`
                ) d
                ON s.sales_area=d.sales_area
                WHERE
                    s.creation_date BETWEEN dt_sim_start AND dt_sim_end
                    AND s.material = target_sku_code
            ) d
            ON
                d.market=s.market AND
                d.material=s.material AND
                d.creation_date=s.creation_date
            where
                s.creation_date BETWEEN dt_sim_start AND dt_sim_end
                AND s.plant IN ("C020", "C021", "C022")
                AND s.material = target_sku_code
                AND s.bad_stock_flag IS NULL
                AND s.good_quality_flag = "GQ"
            group by 1, 2
        )
    UNPIVOT
    (
        value for cod_argument in
            (
                daily_qual_demand,
                daily_net_flow_pos
```

```sql
            )
    )
),
dd_hist_trends_inv as
(
    -- this gives the historical inventory trends as computed by the DDMRP automatic report
    SELECT
        material,
        creation_date,
        cod_argument,
        value
    FROM
    (
        SELECT
            s.material,
            s.creation_date,
            sum(on_hand_qty) on_hand_usable_qty,
            sum(intransit_qty) intransit_qty,
            sum(total_target) tot_target_inv,
            sum(red_zone) red_zone,
            sum(yellow_zone) yl_zone,
            sum(green_zone) gr_zone,
            sum(adu_total) adu,
        FROM `ind-inv-fg.target_stock_history` s
        WHERE
            creation_date BETWEEN dt_sim_start AND dt_sim_end
            AND plant in ("C020", "C021", "C022")
            AND s.material = target_sku_code
            AND s.bad_stock_flag IS NULL
            AND s.good_quality_flag = "GQ"
        group by 1, 2, 3
    )
    UNPIVOT
    (
        value for cod_argument in
        (
            on_hand_usable_qty,
            intransit_qty,
            tot_target_inv,
            red_zone,
            yl_zone,
            gr_zone,adu
        )
    )
)

SELECT
    s.material,
    "Cassinetta Site" as plant,
    s.YEAR,
    s.ISOWEEK,
    s.d_date,
    "daily_demand_trend" as cod_argument,
    value,
    DATE_DIFF(s.d_date, dt_sim.ini, DAY) AS rel_timestamp
FROM dd_dmd_crv s, dt_sim

UNION ALL

select
    t.material,
    "Cassinetta Site" as plant,
    EXTRACT(YEAR from t.creation_date) YEAR,
    EXTRACT(ISOWEEK FROM t.creation_date) ISOWEEK,
    t.creation_date,
    t.cod_argument,
    t.value,
    DATE_DIFF(t.creation_date, dt_sim.ini, DAY) AS rel_timestamp
from dd_hist_trends_qual_dmd_nfp t, dt_sim

UNION ALL

select
```

```
                t.material,
                "Cassinetta Site" as plant,
                EXTRACT(YEAR from t.creation_date) YEAR,
                EXTRACT(ISOWEEK FROM t.creation_date) ISOWEEK,
                t.creation_date,
                t.cod_argument,
                t.value,
                DATE_DIFF(t.creation_date, dt_sim.ini, DAY) AS rel_timestamp
            from dd_hist_trends_inv t, dt_sim
        )
    order by 8, 1, 2;

ELSE

    SELECT
        *
    FROM
        (
            with wk_dmd_crv as
            (
                SELECT
                    material,
                    ref_week,
                    sum(demand_total_qty) value,
                FROM `ind-inv-fg.demand`
                where
                    ref_week BETWEEN dt_sim_start AND dt_sim_end
                    AND plant in ("C020", "C021","C022")
                    AND material = target_sku_code
                group by 1, 2
            ),
            dt_sim as
            (
                select
                    material,
                    MIN(ref_week) ini,
                    DATE_ADD(MAX(ref_week), INTERVAL 6 DAY) lst
                from
                    wk_dmd_crv
                group by 1
            ),
            dd_dmd_crv as
            (
                with dd_cal as
                (
                    select
                        dt_sim.material,
                        l as d_date
                    FROM
                        dt_sim, UNNEST(GENERATE_DATE_ARRAY(dt_sim.ini, dt_sim.lst)) l
                )

                select
                    material,
                    d_date,
                    YEAR,
                    ISOWEEK,
                    (
                      LAST_VALUE(value IGNORE NULLS)
                      OVER (PARTITION BY material, YEAR, ISOWEEK ORDER BY d_date)
                    )/6 AS value
                from
                (
                    select
                        s.material,
                        s.d_date,
                        EXTRACT(YEAR FROM s.d_date) YEAR,
                        EXTRACT(ISOWEEK FROM s.d_date) ISOWEEK,
                        d.value
                    from dd_cal s
                    left join wk_dmd_crv d
                    on s.material=d.material AND s.d_date=d.ref_week
                )
            ),
```

```
                dd_hist_trends_qual_dmd_nfp as
                (
                 -- REVERSE ENGINEERED APPORACH TO EXTRACT NFE HISTORY BY MATERIAL PLANT …
    -- this gives me the historical qualified demand trend input AND the net flow position
                    SELECT
                        material,
                        creation_date,
                        cod_argument,
                        value
                    FROM
                        (
                            SELECT
                                s.material,
                                s.creation_date,
                                SUM(d.qual_ord_qty) daily_qual_demand,
                                SUM(d.nfe_qty) daily_net_flow_pos,
                            FROM `ind-inv-fg.target_stock_history` s
                            LEFT JOIN
                            (
                                SELECT
                                    d.market,
                                    s.material,
                                    s.creation_date,
                                    s.qual_ord_qty,
                                    s.nfe_qty
                                FROM `ind-inv-fg.nfe_by_mat_sales_area` s
                                LEFT JOIN
                                (
                                    SELECT
                                    DISTINCT
                                        sales_area,
                                        market
                                    FROM `ind-inv-fg.external_data.market_to_sales_area`
                                ) d
                                ON s.sales_area=d.sales_area
                                WHERE
                                    s.creation_date BETWEEN dt_sim_start AND dt_sim_end
                                    AND s.material = target_sku_code
                            ) d
                            ON
                                d.market=s.market AND
                                d.material=s.material AND
                                d.creation_date=s.creation_date
                            where
                                s.creation_date BETWEEN dt_sim_start AND dt_sim_end
                                AND s.plant IN ("C020", "C021", "C022")
                                AND s.material = target_sku_code
                                AND s.bad_stock_flag IS NULL
                                AND s.good_quality_flag = "GQ"
                            group by 1, 2
                        )
                    UNPIVOT
                    (
                        value for cod_argument in
                            (
                                daily_qual_demand,
                                daily_net_flow_pos
                            )
                    )
                ),
                dd_hist_trends_inv as
                (
                 -- this given me the historical inventory trends as computed by the DDMRP chart
                    SELECT
                        material,
                        plant,
                        creation_date,
                        cod_argument,
                        value
                    FROM
                    (
                        SELECT
                            s.material,
```

```
                        s.plant,
                        s.creation_date,
                        sum(on_hand_qty) on_hand_usable_qty,
                        sum(intransit_qty) intransit_qty,
                        sum(total_target) tot_target_inv,
                        sum(red_zone) red_zone,
                        sum(yellow_zone) yl_zone,
                        sum(green_zone) gr_zone,
                        sum(adu_total) adu,
                    FROM `ind-inv-fg.target_stock_history` s
                    WHERE
                        creation_date BETWEEN dt_sim_start AND dt_sim_end
                        AND plant in ("C020", "C021", "C022")
                        AND s.material = target_sku_code
                        AND s.bad_stock_flag IS NULL
                        AND s.good_quality_flag = "GQ"
                    group by 1, 2, 3
                )
                UNPIVOT
                (
                    value for cod_argument in
                    (
                        on_hand_usable_qty,
                        intransit_qty,
                        tot_target_inv,
                        red_zone,
                        yl_zone,
                        gr_zone,adu
                    )
                )
            )

            SELECT
                s.material,
                "Cassinetta Site" as plant,
                s.YEAR,
                s.ISOWEEK,
                s.d_date,
                "daily_demand_trend" as cod_argument,
                value,
                DATE_DIFF(s.d_date, dt_sim.ini, DAY) AS rel_timestamp
            FROM dd_dmd_crv s, dt_sim

            UNION ALL

            select
                t.material,
                "Cassinetta Site" as plant,
                EXTRACT(YEAR from t.creation_date) YEAR,
                EXTRACT(ISOWEEK FROM t.creation_date) ISOWEEK,
                t.creation_date,
                t.cod_argument,
                t.value,
                DATE_DIFF(t.creation_date, dt_sim.ini, DAY) AS rel_timestamp
            from dd_hist_trends_qual_dmd_nfp t, dt_sim

            UNION ALL

            select
                t.material,
                t.plant,
                EXTRACT(YEAR from t.creation_date) YEAR,
                EXTRACT(ISOWEEK FROM t.creation_date) ISOWEEK,
                t.creation_date,
                t.cod_argument,
                t.value,
                DATE_DIFF(t.creation_date, dt_sim.ini, DAY) AS rel_timestamp
            from dd_hist_trends_inv t, dt_sim
        )
        order by 8, 1, 2;

    END IF;
END;
```