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Master of Science in Management Engineering

Sustainable Operations Management and Social Innovation

# Application of a Multi-Echelon Safety Stock Optimization Model. Barilla Case Study


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# EXECUTIVE SUMMARY

The thesis work originates from an optimization project carried out in Barilla Group supply chain area, specifically in Supply Chain Network Design department, where I conducted my internship.

The project concerns the application of a multi-echelon safety stock optimization model on Barilla distribution network. To directly address the problem, the project includes the deployment of *Llamasoft Supply Chain Guru*, an integrated optimization software that provides optimization model packages. Supply Chain Guru Inventory Optimization model is investigated and tested for the first time in the company during this project. Specifically, Safety Stock Optimization model is applied with the objective to determine the optimal safety stock level in the network, minimizing the inventory holding cost related to the whole distribution network and to meet a target customer service requirement.

The perspective is not restricted locally to customer-facing stages only, but it includes the whole multi-echelon distribution network, for an augmented and effective safety stock optimization.

*Supply Chain Guru Safety Stock Optimization* consists of two stages. First, demand is studied based on a categorization schema developed by Syntetos and Boylan (2005), which classifies demand according to two variables: intermittency, that is how often demand occurs in a given period, and variation, that is how different in quantity demand occurs in a given period. The mentioned classification framework is enforced in the model to associate a product demand to one of the four demand classes defined by the combination of the two categorization variables. Indeed, based on a two-axis matrix where demand intermittency and demand variation are the variables and specific threshold values for both variables are set, four possible demand classes are outlined: (1) *smooth* demand corresponds to a non-intermittent and stationary demand, (2) *erratic* demand defines a non-intermittent and highly variable demand, (3) *slow* demand represents an intermittent and low variable demand and (4) *lumpy* demand occurs as non-intermittent and highly variable demand.

Demand analysis and classification anticipates safety stock optimization, so that demand statistics are computed, and lead time demand distribution may be defined, according to the demand class, becoming input information for the subsequent step.

Once demand analysis has completed, the second stage, multi-echelon safety stock optimization, starts. Multi-echelon systems require appropriate optimization models that includes the interdependent variables in the analysis, providing with an effective optimized output at the whole network-level. Simchi-Levi and Zhao (2012) argue that three drivers have brought to positive results in the adoption of multi-echelon inventory optimization approaches: (1) the data availability about demand and lead time, (2) industries' interest in implementing scientific methods in inventory management and (3) latest development of models and algorithms focused on inventory control in general multi-echelon systems.

Specifically, in Supply Chain Guru software, Safety Stock Optimization is based on Graves and Willems (2000) Guaranteed-service model. Graves and Willems approach assumes that every stage quotes a guaranteed service time to its immediate downstream stage, after which the requested item is available. The service times are the decision variables of the model objective function that minimizes the inventory holding cost at all network levels, to meet a target customer service requirement. The result is an optimal safety stock level assuming a holistic supply chain perspective.

The model has been built, entering input data concerning actual sourcing network, replenishments, lead times and costs. Demand has been entered as historical demand series, with the objective to test demand analysis functionality on actual demand information. The plan is to substitute historical demand with forecast demand information, for the operating need to assess the optimal safety stock level given the expected demand, with the corresponding forecasting error, in the future period.

The applied multi-echelon safety stock optimization model should be evaluated by Barilla supply chain planning unit, considering the existing single-echelon safety stock optimization method implemented so far in the inventory planning unit. At the current project phase, a quantitative analysis of model results has not been feasible, since the multi-echelon-based model works with demand input information that are actual historical data, while the single-echelon-based method is founded on forecast demand data. The asymmetry of input data between the two methodologies led to the impossibility to run a quantitative analysis of results and a model evaluation at this project phase.

Nonetheless, Supply Chain Guru optimization model appears a significant resource for future inventory planning processes for qualitative considerations. Demand analysis integrated with safety stock optimization allows the understanding of demand patterns for a more accurate determination of stock levels. The operating role potentially covered by the new optimization model may be combined also with a strategic role: the tool structure enables what-if analysis concerning the inventory network. Thus, although the actual model validation has not been carried out so far, the project has brought to a significant acquaintance with the software logic and with the optimization model construction that frame the multi-echelon safety stock optimization model as potential key resource for the development of inventory planning in Barilla network.

# CHAPTER 1
# CASE STUDY: BARILLA

## 1.1 Introduction

Barilla Group is an Italian company operating in the food sector at global level. Specifically, two business areas are defined within the company: meal solutions, including pasta and sauces, and bakery. With a turnover of 3,468 million Euros in 2017, the Group stands out as leader for pasta worldwide, for sauces in continental Europe, for bakery in Italy and France and for crispbread in Northern Europe.

Meal solution business represents the major business area for sales, counting for 53.9 percent of annual turnover. Bakery, concentrated mainly in Italian and French markets, contributes to 45.6 percent of company's turnover. The remaining 0.5 percent of sales is obtained by other business areas. (Barilla Sustainability Report 2018).

The Group products are clustered among 13 brands and marketed in more than 100 countries. Twenty-eight production sites are located in 9 countries, to meet the global demand.

At geographical level, company's main market is Italy, which contributes to 45,3 percent of turnover, followed by U.S., France, Germany, Turkey.

## 1.2 Food Industry: an Overview

The food represents a strategic arena for the Italian manufacturing sector: composed of 58413 firms located in the national territory, it generated a turnover of 137 billion Euros in 2017 (ISTAT).

It has the second ranking position in the Italian manufacturing sector, after metalworking, impacting on total industry turnover by 12%.

Besides, Italian food production has increased by +1.7% in 2017 compared to the previous year, clearly confirming the economic upswing observed in the latest years. The main driver of the sector economic revamping is the rise in exports: in 2017 Italian food exports reached almost 32 billion Euros, weighing almost one fourth of the total industry turnover and in the last decade exports recorded a 75-percent upturn, three times higher than the total food industry value growth.

European Union countries mainly pull Italian food export (almost two thirds of the total value), while U.S. is the main extra-EU market. The recent results demonstrate that food industry plays a key role as "Made in Italy" ambassador and that the foreign markets represent more and more an encouraging arena for Italian food sector.

To briefly disclose the supply side of agri-food sector may be oversimplifying, due to the width of its good range. Since Barilla operates in sectors that mainly deal with agricultural sectors, such as cereal sector (for semolina and soft wheat flour), its underlying supply chain structure is presented below.

Pasta industry, part of cereal macro-sector, implies (1) durum wheat grain production and commercialization, (2) semolina production and (3) pasta production.

Durum wheat producers and their different collective entities (such as agricultural consortiums, associations and cooperatives) sustain the production and the commercialization of the basic agricultural product. Also private traders, supported with wheat storage structures, are key players in the commercialization phase.

First processing sector includes the durum wheat milling and the production of flours. From this process bran results as a by-product and it is generally dispatched to animal feeding.

The second processing sector is composed of pasta producers (both industrial and artisan). Pastry and bakery producers, differently, use soft wheat flour as main raw material.

The commercialization and distribution occur mostly through the Mass Market Retailers and it is often managed directly by big pasta industrial groups with the production for private labels.

## 1.3 Barilla History

*"Basically, we are pasta makers and bakers; this is the line of work our family has pursued over the last four generations, with the help of outstanding coworkers. It is the only line of work we can and try to improve every day"*

*Guido Barilla*

Barilla was founded in 1877 by Pietro Barilla, who opened a bread and pasta shop in Parma.

In 1910 industrialization was carried on by Pietro's sons, Gualtiero and Riccardo, with a 80-worker factory, which had a production capacity of 8 tons of pasta and 2 tons of bread per day.

In 1936 Pietro, Riccardo's son, launched the commercial network and six continuous presses were introduced, aggregating kneading machine and press functions for the first time.

Since the end of World War II the company faced a period of change, which led to the path to become the first food company in Italy. Gianni and Pietro Barilla organized the corporate management in a structure manner: Gianni focused on production and administration, while Pietro dealt with market and public relations and communication.

In the same years, the company strategy decide to free production from state supply, especially dedicated to Italian army, and to focus on commercial market only.
The business decision implied a reshaping, specifically in management mind and this brought Pietro to fly to U.S., to look for new stimuli.

Back to Italy after two years (1952), three relevant and brave decisions were taken at business level:

- Interruption of fresh bread production, to favour the exclusive focus on durum wheat and egg pasta brands;
- Sales network strengthening and a modern distribution network development;
- Starting a generous investment policy on communication and advertisement, aimed at shaping an established and sticky logo.

Barilla distribution network evolved also due to the development of national highway network.

From the production point of view, several key changes occurred. In 1957 the existing production site was rebuilt, and in 1965 a new factory was introduced in Rubbiano, located in Parma district, for bread stick and rusks production. Italian market responds confirmed Pietro Barilla's insights and in 1968 a new plant was built in Pedrignano with the most modern pasta machineries at that time (it consisted of a 120-meter-long production line).

In the early seventies, Barilla brothers decided to sell the majority of capital to an American multinational corporation, Grace, as a consequence of a critical moment spread in the whole country.

Corporate expansion strategy did not stop: *Voiello* entered the company's brand portfolio and a mill in Altamura (in Puglia region) was acquired. In 1975 *Mulino*

*Bianco* brand was born, marked with a typically American style, based on product diversification. Since its introduction, the brand had been conceived for sweet bakery, rusks and breadsticks only. In 1977 it included also sweet snacks, cracker and "*Pan Carrè*" (sliced bread).

The product mix expansion with short-shelf-life items determined a restructuring also at distribution level, to guarantee a higher customer replenishment frequency.

In 1979 Barilla shares were bought back by Pietro, who gave rise to a new development phase. First, he wanted to revamp pasta, with innovative communication campaigns. He promoted many acquisitions, both in Italy (*Pavesi*) and abroad (*Misko* and *Filiz*). In 1993 Pietro was succeeded by his three sons – Guido, Luca and Paolo, who followed father's business expansion strategy, acquiring *WASA*, a leading brand in dry bread industry, and opening the first pasta production plant in U.S. in 1999.

The new millennium started with another acquisition: *Harrys*, a strong brand in French soft bread industry (2003). In parallel company's entrepreneurial mind-set sought new opportunities in non-core businesses, founding *Academia Barilla* in 2004, an international project focused on Italian culinary culture safeguard and promotion. Pursuing the mission to embody and spread Italian cuisine in the world, Barilla opened some Barilla Restaurants overseas. It is remarkable to mention also Barilla's visionary spirit and social commitment that led to the birth of *Barilla Center for Food & Nutrition Foundation*, a scientific research hub aimed at studying food and its connections with social, economic and environmental sustainability for the promotion of wellbeing and health of people and Planet.

## 1.4 Barilla Brands and Products

Barilla offer is classified in two main business areas:

- *Meal Solutions*: pasta, sauces and ready meals;
- *Bakery*: sweet and savoury bakery products.

Pasta can be further divided in different categories:

- Durum wheat semolina pasta (long-cut, short-cut, spoon pasta)
- Egg pasta (lasagne, noodles and tortellini)
- Whole wheat pasta
- Five-cereal pasta

Sauces are divided in the following typologies:

- Ready sauces;
- Red Sauces (Tomato-based);
- Pesto;
- “Pestati”;
- Ragù or Bolognese sauces.

Bakery encompasses a varied assortment of products, such as:

- Biscuits;
- Rusks;
- Soft bread;
- Sweet and savoury snacks;
- Cakes;
- Crackers.

In **Meal Solutions** market Barilla Group owns several brands.

*Barilla* is the global established brand for pasta and sauces. It is symbol of quality, Italian style and wholesomeness worldwide.

*Voiello* was born in 1879 as small pasta shop in Torre Annunziata, located in Naples area. The brand is an icon for Neapolitan pasta tradition, retraced in the shapes and durum wheat quality. It is perceived as a premium brand in pasta market and it entered in Barilla brand portfolio in 1973.

*Filiz* is one of the top pasta producer in Turkey, and it has belonged to Barilla Group since 1994.

Since 1927 *Misko* has been a Greek established pasta brand. Symbol of local tradition and quality, it was acquired by Barilla Group in 1991.

*Yemina* and *Vesta* are two brands in Mexican pasta market, respectively since 1952 and 1966. They became Barilla-owned brands following a joint venture with Herdez Group in 2002.

*Casa Barilla* is an Italian fast casual restaurant chain expressing the best of Italian cuisine at affordable prices. Launched in New York City in 2013, Casa Barilla Restaurants serve wholesome meals in three locations in New York and in two locations in South California.

*Academia Barilla* was born in 2013 as culinary institute and divulgation center for Italian gastronomic heritage. It offers food specialties, books, cooking classes and food tours.

*Cucina Barilla* is a brand for a new e-business focused on the commercialization of a unique smart oven and ready-meals that can be prepared with it.

**Bakery** products are gathered under the following brands:

*Mulino Bianco* was established in 1975 and since then it has been part of Italian food culture and of Italian families' diet. This brand is marked by simple, wholesome bakery products in all categories.

*Pavesi* brand was founded in 1937 by Mario Pavesi, an Italian inventive baker and entrepreneur in the city of Novara. The wide range includes sweet and savoury bakery products and pastries, recognized by a unique taste and that rely on well-developed production technologies. In 1992 Barilla acquired the brand.

As leader brand in soft bread and breakfast goods sector in France, *Harry's* has two main key success factors: innovation and quality. Five plants are located in France and dedicated to *Harry's* product line manufacturing.

Founded in 1919 in Sweden, *Wasa* is one of the strongest brand in crispbread sector, especially in Northern Europe markets. Barilla acquired it in 1999.

*Pan di Stelle* was launched in 1983 as Mulino Bianco breakfast biscuit. Since 2007, it has become a stand-alone brand with the introduction of sweet snacks and a cake, marked with *Pan di Stelle* uniqueness.

*Gran Cereale* is the father of whole grain and natural biscuits, born as part of Mulino Bianco's family in 1989. Today the brand offers a wide range of different bakery products, including muesli, sweet snacks and biscuits.

It is important to mention also *F.I.R.S.T. Retailing S.p.A.*, a specialized structure that operates in retail services.


Figure 1: Barilla Group brands divided in (from right) Meal Solutions, Bakery and other brands

## 1.5 Barilla Supply Chain Profile

Fisher (1997) considers a double function of a company supply chain. The *physical function* is linked to physical process and flow, including the transformation from raw material to finished goods and distribution. The second function is *market mediation* that aims at granting that supply variety matches market requests.

Fisher (1997) constrains its model to demand uncertainty only, which generates two possible effective supply chain strategies: an *efficient supply chain* may be applied to functional product, whose demand is steady and therefore predictable with a long product life cycle, while a *responsive* one is suitable for innovative products, which present a relatively short product life cycle and fluctuating demand.

Lee (2002) offers an augmented framework based on Fisher's study, adding supply uncertainty as variable to assess the optimal supply chain strategies.

Product supply side may be classified as either *stable* or *evolving*. Mature manufacturing processes and technologies together with rooted supply bases characterize a stable supply. Differently, an evolving supply is exposed to systematic changes and so it has to cope with remarkable complexity at technological level and higher uncertainty at margin level.

In Barilla the supply chain is responsible for designing, developing and managing the industrial network needed to support the company's strategy, and thus it assures:

- A profitable and innovative business development;
- The maximization of return on investment;
- The target service level for customers and the target safety and quality for its products.

Lee's framework can be applied to Barilla supply chain, to disclose the key features characterizing both company's supply and demand and to consider the appropriate supply chain strategy.

Demand side can be analysed both in terms of product characteristics and in terms of demand patterns. Barilla, operating in agri-food sector, deals with a mature environment where demand is relatively steady and predictable compared to other businesses. Nonetheless, although the product demand at end-consumer level results not fluctuating, Barilla position along the supply chain exposes it to bullwhip effect, which can be expressed as the amplification of order variability as one goes upstream in the supply chain (Lee, 2000). Barilla, as manufacturer, falls into demand patterns that result more erratic than the ones faced by retailers.

Since the nineties the Italian company has attempted to mitigate demand uncertainty with the implementation of a collaborative supply chain planning with customers, specifically Vendor-Managed-Inventory system. Barilla is responsible for managing planning processes of its major clients (all large retailers in Italy and few retailers in France, Belgium and Switzerland), reducing clients' procurement and planning costs and granting a higher service level through a complete supplier's visibility on demand, stocks, promotions data. Barilla benefits from a centrally coordinated supply chain model since the upstream bullwhip effect is largely mitigated and consequently it can perform more efficiently (logistic cost decrease) and effectively (ensure a higher service level).

Besides the characteristics of demand, demand uncertainty is related to the type of product the company deals with. Barilla product range width is about 8000 SKUs, a medium value that yields complexity. Product life cycle is on average long: being the agri-food sector not characterized by short-selling season, food products have on average 5-year-long life. Barilla products generally have a low profit margin and a low obsolescence risk.

The demand-related drivers reveal that Barilla is positioned on the left-handed quadrant with respect to demand uncertainty axis.

From the supply point of view, Barilla exposure is restricted to raw material supply and to finished good supply, for the outsourced production.

In pasta industry Barilla adopts a vertical integration strategy: durum wheat is purchased from local suppliers, which is stocked and afterwards milled internally to make up specific semolina mixtures for pasta production. Only 20% of total dry semolina volume comes from external sources, for flexibility purposes. Barilla purchasing strategies favour the selection of local raw material suppliers, located in the areas of mills and plants. Raw materials purchased by the company are mainly food products, such as wheat, flour, tomatoes, cocoa and so they are not based on complex manufacturing processes and they are not exposed to technology evolution.

Durum wheat is the major raw material purchased by the company (37% of purchase value) and it represents the quality input for Barilla finished product (based on a semolina and water dough). The company developed *Barilla Sustainable Farming* policy that promotes more efficient cropping systems, in order to obtain safe and high-quality agricultural products, protecting and improving the environment and the social and economic conditions of farmers. An integrated supply chain relies on collaboration with farmers, supported in planning multiyear sustainable cultivation systems and guaranteeing commercial possibility to all the products of the crop rotation. The raw materials, on which *Barilla Sustainable Farming* is active, are cereals (durum wheat, soft wheat), tomatoes (for sauces), sugar and vegetable oils. In 2015 Italy *Barilla Sustainable Farming* project resulted in a 26% durum wheat valuable production improvement (measured in Euros/hectare), and a 6.4% direct cost reduction (measured in Euros/hectare), beyond the environmental impact reduced by 8.3% (Carbon Footprint measured in $CO_2$ tons/Durum Wheat tons). The benchmark analysis was performed with common cropping systems.

Following Lee's Framework, Barilla supply chain profile could be positioned in the upper-left quadrant facing relatively low uncertainty both from demand and supply side (Figure 2).

The recommended supply chain strategy emerged from Lee's model is the lean strategy, which is in line with the actual company's supply chain strategy. Indeed, the centralization of the global supply chain management in the headquarter demonstrates the will to control and to optimize all the supply chain processes. Moreover, the main projects carried out by supply chain planning divisions are focused on optimization. Safety stock optimization project belongs to a set of initiatives that pursue a cost minimization objective.

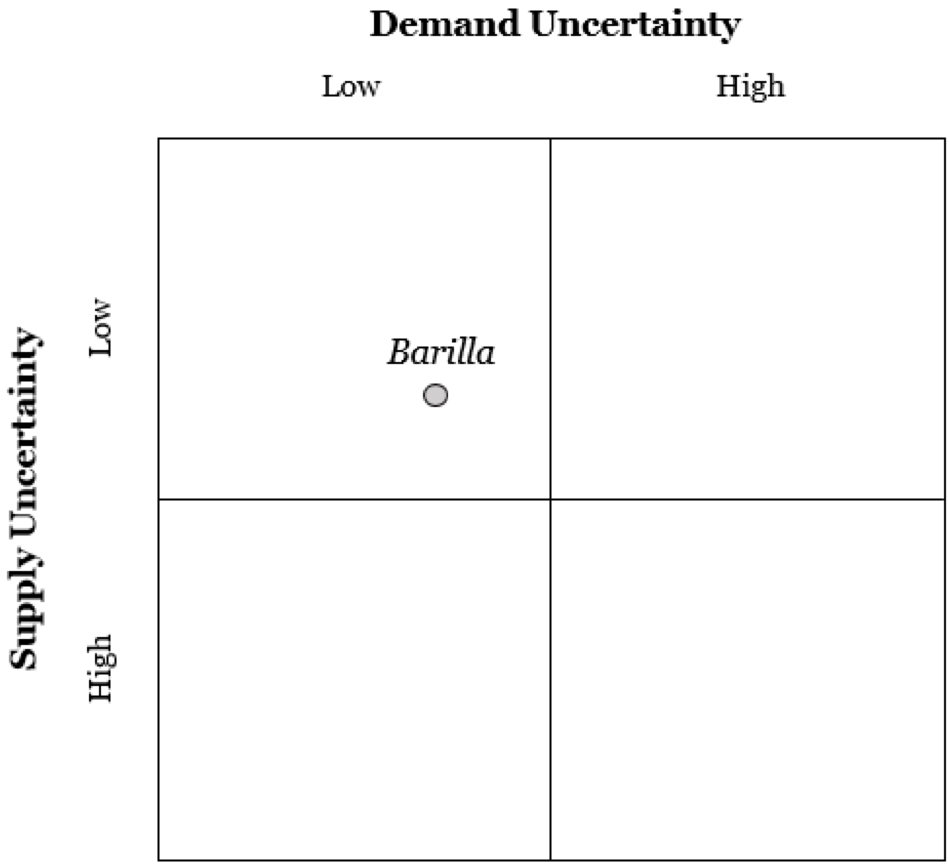



Figure 2: Graphical representation of Lee's Model adopted for analyzing Barilla supply chain strategy.

## 1.6 Barilla Supply Chain Organization Structure

The business process units embedded in Barilla Group Supply Chain are the followings.

*Operations and Manufacturing Strategy*

This business unit is responsible for designing manufacturing objectives and for allocating capital investment based on the set priorities. It also defines production structure components, such as the resources, the processes and the IT services.

*Supply Chain Design, Planning and Customer Service*

Logistics network structure – supply, production and distribution network – is responsibility of this business unit. Specifically, the planning function is performed at daily level for operating activities (for instance the daily transportation planning), at tactical level (for instance the identification of optimal level of stock), and at strategic level (for instance the identification of facilities location).

Recalling Lee's studies, the fragmentation of supply chain planning process consists in the disaggregation of core planning activities, carried out by several players along the supply chain, thus it consists in the creation of more than one decisional centers that make decision individually even if they belong to the same supply chain (Lee et al., 1997).

*Logistics*

This business unit coordinates and manages the outsourced logistics services. The responsibilities are to monitor the activities performed by external logistics providers, through performance evaluation, benchmarking and control.

*Purchasing*

The activities under the responsibility of this business units are related to the upstream supply chain and specifically they are the selection of new potential suppliers, the vendor rating activity, through the suppliers' performance evaluation. Moreover, purchasing unit identifies the impact of law and regulations and develops benchmarking activity implemented on existing suppliers.

*Technical Development*

It is responsible for the development processes of company's production plants. It coordinates and manages maintenance, plants' tests, packaging standardization and installation activities.

*People, Safety, Environment and Energy*

This business unit outlines both short-term and long-term actions required to guarantee company's activity sustainability concerning Health and Safety, Fire Prevention, Environment and Energy.

## 1.7 Barilla Distribution Network

Barilla has a mixed distribution network consisting of two levels, based respectively on primary and secondary transportation.
Plant warehouses, representing the central warehouses, are connected both with hubs and customers' distribution centres through primary transportation. Pure direct flows and mixed direct flows to customers represent more than three quarters of shipped volumes in Italian market.

At this level transportation is carried out with FTL (Full Truck Load) shipments, through a semi-trailer (or a trailer). For logistics cost optimization reasons, trailers are accurately loaded to maximize either volume or weight saturation[1], compatibly with customers' orders and hubs' replenishments. Direct shipment is the main channel for vendor-managed-inventory system, a collaborative supply chain approach implemented by Barilla since the nineties with some big customers. This system involves not only the national distribution, but also the distribution of some European customers.

One-echelon distribution network is the second most exploited approach to serve customers and it is based on regional warehouses, generally called *hubs*. Regional warehouses have a main role in postponing the order preparation along the network, decreasing the order cycle time and also primary transportation costs.

[1] Depending on transportation mean typology there are both weight and volume limitations. For example, the maximum weight for trailers allowed by Italian law is 25 tons.

Indeed, the whole product range is stocked in regional warehouses, since they are strategically located to serve the demand of a defined geographical area. Differently from most plant warehouses, which are used to stock products coming from the bordering plant, hubs are used to raise product range consolidation, being replenished periodically by all production sites, co-packers and auxiliary warehouses. Auxiliary warehouses represent extra storage area temporarily rented by the company to deal with demand picks during specific periods of the year. They are usually located in strategic areas close to central or regional warehouses, in order to minimize transportation costs.

Second-echelon distribution network is composed of transit points, since the main driver is represented by secondary transportation cost reduction. This type of distribution is carried out with Less Than a Full Truckload that allows frequent hauls for delivering small-sized orders.

Although secondary distribution has a cost per transported unit higher than primary one, it allows benefits in terms of flexibility of both carried volumes (primary distribution is restricted to loaded material levels higher than some standards defined by the company's strategy) and accessible locations (articulated lorries used in primary distribution have big dimensions, which are not always compatible with customers' warehouses).

Shorter travel distances of secondary transportation are permitted by strategic hub and transit point allocations to serve a certain customer geographical area. Barilla does not manage the second-echelon distribution, but by external logistics providers do.
To complete Barilla distribution network outlook, it is necessary to remark the role of co-packers. The company strategy relies on outsourcing part of production to cope with limitations either on production capacity or on production technologies (for instance, gluten-free products have strict requirements in terms of technologies and their production is sourced from selected suppliers). Indeed, co-packers are specific suppliers of either semi-finished or finished goods, and they respond to strict and specific terms, explicitly required by Barilla.

Co-packer presence affects negatively distribution network complexity, since it has to deal with two extra types of flows:

a. Direct flows from co-packers to plant warehouses, which are central warehouses (especially when supplied goods are semi-finished and so components, which will be further reworked in plants);
b. Direct flows from co-packers to hubs (although they occur occasionally).

Figure 3 shows a mixed network that may be representative of Barilla's distribution network structure (although the number of elements does not correspond to the real one).

It consists of:

- Plants (most of them supported by internal warehouses, in light blue);
- Auxiliary warehouses that are exploited for limited time periods to gain extra storage capacity;
- Co-packer plants from which products are moved either to plant warehouses or hubs or customers;
- Regional warehouses (or *hubs*);
- Customers, who are distinguished between big retailers (with their own distribution centres, in green), and smaller ones (with minor points of sale, represented by the cart in Figure 3).

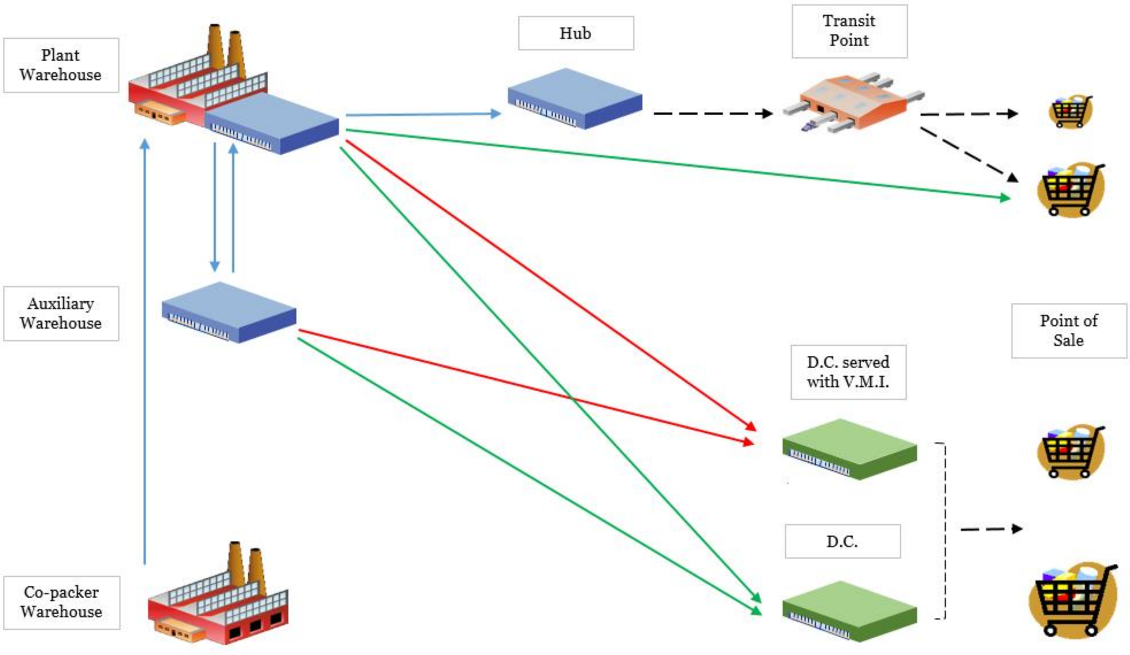



Figure 3: Barilla Distribution Network.

The figure structure defines also the connections among the different nodes:

- Blue arrows stand for stock transfer orders (STOs), hauls to replenish hubs or auxiliary warehouses and hauls for receiving goods from outsourced production.
- Red arrows are optimized orders, managed through vendor-managed-inventory system that implies direct shipments from central warehouses to customer distribution centers.
- Green arrows stand for traditional orders, not handled through a collaborative supply chain approach but still based on primary transportation. Traditional orders are fulfilled either by plant warehouses or auxiliary warehouses.
- Dotted arrows are orders not managed by Barilla, but by external logistics providers that exploit their transit points to reach the final points of delivery.

## 1.7.1 Production Plants

Barilla Italian production network is made up of 10 plants[2] (mills dedicated to durum wheat semolina production are excluded) and each of them is specialized in only one of company's product categories:

- *Meal solutions* (four plants);
- *Bakery* (six plants).

Meal solution plants are further divided in three pasta plants and one sauce plant. To comprehend Italian Barilla production network, Figure 4 shows Italian map populated with production sites specifically marked with different colours, according to the type of production (as reported in the legend below).

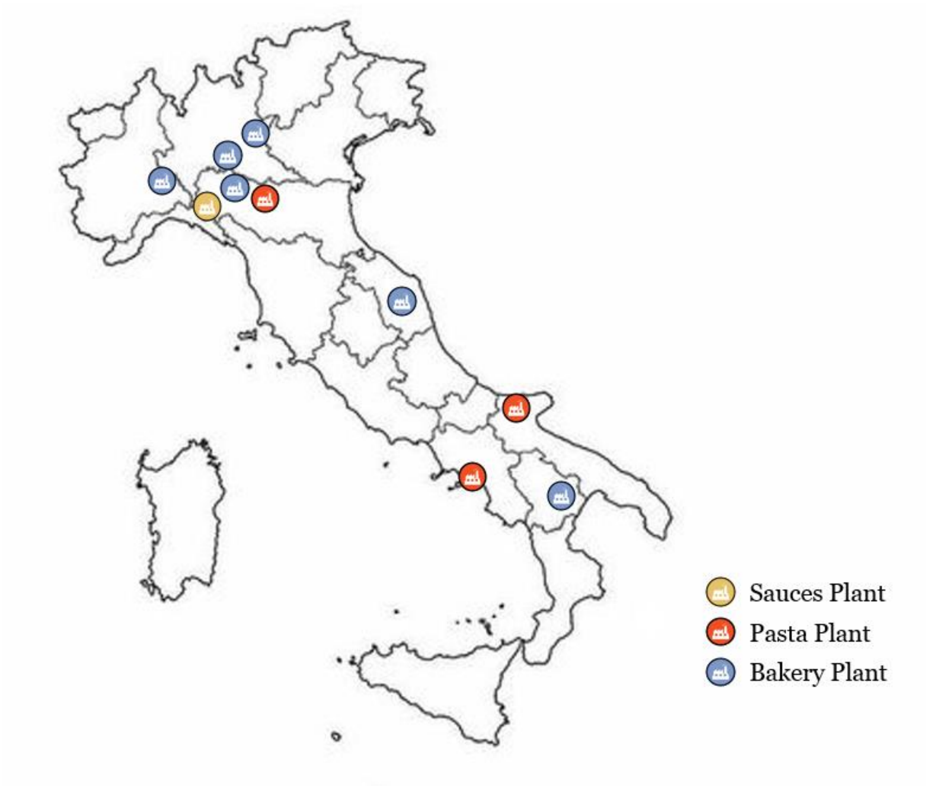



Figure 4: Barilla Production Network in Italy.

[2] In Rubbiano site there are two separate buildings, one dedicated to sauce production and the other one to bakery.

In addition to Italian sites, Barilla network includes 12 production plants in the rest of the world, located specifically in France (dedicated to *Harry's* bakery production), Germany, Sweden (for *Wasa* dry bread production), Greece, Turkey, Russia, U.S. and Mexico (for pasta production). Most plants aim at satisfying the demand of their own geographical area (also with specific products).
As previously mentioned, internal production is supported also by external producers, called co-packers. The decision to outsource production sometimes is related to new launched products, that need to test the market and their profitability for a potential in-house production. Company strategy adopts a *buy option* rather than a *make option*, generally when demand level is not high enough to justify the internalization of specific production processes, but it is positive enough to be achieved through an outsourced supply.
Outsourced volume weighs on global Barilla production for less than 10%, and it is sourced from several co-packers worldwide (mostly located in Italy).

### 1.7.2 Hubs

Regional warehouses/hubs in Barilla network are located in multiple local demand areas and they are designed especially for a prevalent picking function (the selective retrieval of unit loads from high-level unit loads or single pieces/cases from racks or plastic crates, for the customer purchase order fulfilment).
Their strategic role stands in the ability to ensure an average three-day order dispatching time, differently from auxiliary and central warehouses that generally have longer order-cycle-times.
Barilla second distribution network level consists of 12 hubs in Europe. In Italy seven hubs have been located with the objective to optimize distribution flows, constrained by production sites and final delivery points. Figure 5 illustrates Barilla regional warehouses in Italy.


Figure 5: Barilla Regional Warehouses in Italy.

The main drivers behind the decision to implement a second level of regional warehouses in the network are:

a. To guarantee an adequate service level in terms of time. By positioning stocked items closer to the final destination, Barilla can serve customers in shorter time frame. Order-cycle-time on average decreases.
b. To cut secondary transportation costs. Customer orders may be fulfilled with the hub stocked items, making the order processing start closer to final destinations.
c. To ensure an adequate service level in terms of availability to replenish small customers with the whole product range.

While points (a) and (b) of the list above are very intuitive, point (c) may require an additional disclosure. Both plant warehouses and auxiliary warehouses store mostly their "own" products (or the products of plants that replenish auxiliary warehouses). On the contrary, each hub is replenished by all plant/auxiliary

warehouses, in order to meet the demand allocated to that specific hub. Thus, hubs contain generally the complete product range available for the distribution to customers. Indeed, the items managed by Barilla hubs are on average 800, with slight differences due to some distinct phenomena (for instance, products dedicated to specific geographical areas increase or reduce the number of handled trade units in a specific location).
In conclusion, following the points raised about Barilla distribution network, it seems clear that it reveals both strengths and weak elements. From one hand the stock fragmentation along multiple distribution levels allows great flexibility in terms of availability and delivery time, but on the other hand this causes higher inventories and handling costs, raising complexity in managing the distribution network (due to motion of goods from first to second network level).

Specifically, the present work aims at assessing the optimal safety stock level in Barilla hubs, in order to guarantee the target service level, expressed in terms of order fill rate, acknowledging the complexity of both the examined network and demand.

# CHAPTER 2
# CURRENT INVENTORY MANAGEMENT AND PLANNING SYSTEM

## 2.1 Current Inventory Management and Control System

Inventory management represents a key issue for companies, since it concerns the assessment of the quantity to produce/order and the time to start the production or to issue the order. In Barilla the inventory planning system is based on *Time Phased Order Point* (TPOP), a technique that determines the inventory quantity to order, considering both forecasted orders and actual client orders.

This approach results appropriate for finished products with an independent demand, which are all goods, whose demand derives solely and directly from the market requests, or which are functional to production processes, but not necessarily related to the finished product quantity (for instance, the lubricant for machineries is a material with independent demand).

Independent demand, being pulled by the market, must be estimated for production-related and inventory-related reasons.

TPOP system is based on the assumption that the inventory replenishment should be executed when the available inventory level results insufficient to guarantee the fulfilment of future requests. To determine the inventory level, both actual client orders and forecasts are considered in the analysis. Forecasted volumes are defined also taking into account external factors, such as seasonality, trends and promotions.

Besides, *Time Phased Order Point* (TPOP) is a computerized replenishment technique that assumes the time horizon partition in single periods, known as time buckets, which can be day or week long. The tool structure is based on *Material Requirement Planning* (MRP), which determines the quantity of each single required component, based on the bill of materials of finished products and on the production plan.

Nonetheless, while MRP technique is implemented on items with dependent demand, which derives directly from the master production schedule, (for instance item codes included in finished good bills of materials), TPOP approach can be applied also to products with independent demand.

Specifically, TPOP permits to manage stocks considering future product demand without referring to a reorder point. Using this technique, information are organized in tables and partitioned along time buckets (Table 1).

| **Time Bucket** | 1 | 2 | 3 |
|---|---|---|---|
| **Forecast Requirements** | | | |
| **Scheduled Orders** | | | |
| **On Hand** | | | |
| **Planned Shipments** | | | |

Table 1: TPOP technique structure

In view of an actual need, the replenishment order is executed considering both the scheduled orders and the inventory on hand, so that the latter does not drop below the defined safety stock level.

The main advantage linked to TPOP system is the visibility about the demand as far as the time planning goes. Indeed, in fixed-order size systems replenishment orders are triggered by a pre-defined order point and this procedure implies to keep a certain quantity of stock although it is not actually needed. Differently, TPOP can dynamically schedule demand and supply information, and, based on these input data, it recommends new order actions. TPOP can handle forecast errors and variations in demand very good, while holding stock level low (Martin, 1995).

A relevant information to take into consideration is the replenishment lead time, since the replenishment order should be scheduled so that the ordered quantity is replenished exactly when the inventory level goes below the set safety stock level. The necessity to include the time factor in the stock replenishment planning is a key characteristics of *Time Phased Order Point* technique.

The implementation of the inventory planning technique occurs through the use of information systems such as SAP APO (*SAP Advanced Planning and Optimization*), which is a SAP specific module that offers an integrated set of functionalities to plan and execute supply chain processes.

Based on some input data, the system elaborates the DRP (Distribution Requirement Planning) daily, which provides the basis for integrating supply chain inventory information and physical distribution activities with the manufacturing planning and the control system (Vollman 1997). Specifically, DRP aims at determining which products, in which quantity and in which locations, are required to move to meet a certain future demand (partially expressed through the actual orders entered by Barilla customers in *SAP* and partially expressed as forecast demand). The overall objective is to minimize stock-outs, to reduce order costs, to optimize transportation and to minimize stock level.

The input information required by the inventory planning system are the followings:

a. The forecast demand;
b. The available inventory level;
c. The target inventory level;
d. The replenishment lot size;
e. The replenishment lead time considered as the elapsed time between the client order submission and the order arrival at the replenishment destination site.

Given the available stock levels in the locations, the system performs a subsequent automatic process, called *deployment* that either confirms or denies the replenishment requests generated with the DRP. After the confirmation of the needed replenishments, the available stock levels are allocated to all hubs.

## 2.2 Current Safety Stock Optimization Model

The necessity to have a method for assessing the optimal stock level is clear, since the target stock level is a required input information for the inventory planning process, disclosed in section Capitolo 2. Specifically, in the existing inventory planning system an ad-hoc developed model determines the safety stock level in Italian regional warehouses.

The mentioned model is based on Hadley and Within safety stock formula, which assumes both demand and lead time as two stochastic and independent variables. Specifically, the existing model determines safety stock level as a function of forecast demand, forecasting error, replenishment lead time and its variability, subject to the target service level.

The decision regarding the substitution of historical demand with the corresponding forecast demand was mainly driven by the fact that the considered items are highly sensitive to commercial activities such as promotions. Thus, since the inclusion of historical demand could not take into consideration all future demand patterns, forecast demand resulted a correct input parameter for the estimation of safety stock level.

Moreover, some specifications about replenishment frequency should be outlined. The inventory review for Barilla regional warehouses occurs with a daily frequency. Nonetheless, replenishments are not carried out necessarily every day to all locations, mainly because some regional warehouses are located at relatively long distances from the sourcing points, and so daily replenishments to these sites would result too economically demanding. The decision to perform replenishments to these warehouses, deals with the comparison between the transportation costs (with a narrow focus on truck unsaturation cost) and the cost of lost sales due to stock-out. If unsaturation cost results by far higher than the lost sale cost, the replenishment is put off, pending new orders placed by the considered destination.

Based on the disclosed as-is environment, replenishment frequency emerges as a key parameter to include in the estimation of stock level. In the existing safety stock optimization model a periodic inventory control system is assumed under the hypothesis that a period $T$ could reflect the average time elapsed between two replenishments at the same destination site.

The following equation presents the safety stock (SS) formula applied to a periodic control system, used in the model:

$$SS = k * \sigma_{D,LT+T}$$

$\sigma_{ED,LT+T}$ represents the standard deviation of forecasting error during period $LT + T$.

Specifically $\sigma_{ED,LT+T}$ can be expresses as:

$$\sigma_{ED,LT+T} = \sqrt{MSE * (LT + T) + \sigma_{LT}^2 * ED^2}$$

Where

- $k$ represents the value of the standardized variable $z$, to which corresponds a certain cumulative probability equal to the service level.
- $ED$ is the forecast demand,
- $MSE = \frac{1}{n-1}\sum(D_t - F_t)^2$ , expressing demand unpredictability,
- $LT$ is the replenishment lead time
- $\sigma_{LT}^2$ expresses the lead time variability
- $T$ is the average time elapsed between two replenishments.

$k$ value, the service level factor, is equal to the standardized variable $Z$, derived from the demand mean in the period ($\mu$) and from the demand standard deviation ($\sigma$), as showed in the following formula:

$$Z = \frac{x - \mu}{\sigma}$$

In practice the determination of $Z$ value is done through empirical tables that relate Z value to the corresponding cumulative probability, representing the stock-out probability. Given the target service level, which must be selected in a way that it is in line with the company strategic objectives, k value can be determined with the explained methodology.

The following assumptions are true for the development of the existing safety stock model:

- The distribution of the demand is normal;
- The cost of order issuance is constant;
- The production cost is constant;
- The stocking locations has no storage capacity constraints.

In short, the safety stock optimization model implemented so far is explained by Figure 6, with the corresponding model input information (pointed out with blue arrows) and the model output (pointed out with the red arrow).


Figure 6: Current Safety Stock Optimization Model.

## 2.3 Criticalities of the Existing Model

The current model for determining the optimal safety stock level in Barilla regional warehouses results to be the first structured methodology implemented in the company for that purpose. In short, it is a single-echelon safety stock allocation model, based on the assumptions that demand and lead times are stochastically independent variables in the system and that demand is normally distributed. Besides, it assumes a periodic inventory control system, to express replenishment frequencies that vary depending on the specific replenishment lane in Barilla network.

Analysing the model structure and underlying assumptions, some critical points emerge.

First, normally distributed demand is an assumption valid for the whole range of items in the model, which includes different items both from a product-life-cycle perspective and from a sales volume perspective. Indeed, the considered set of items comprises items with relatively homogeneous demand in terms of quantity and demand occurrence, but also other items, with either shorter life-cycles or demand seasonality or further factors that affect their demand pattern making it not normally distributed. Thus, the assumption of demand normal distribution may fit many items considered in the model, but could not be appropriate to represent demand distribution of other items, whose demand presents significant variations in terms of quantity and in terms of occurrence.

Second, the implemented safety stock optimization model is based on a single-echelon system structure, which considers only the key parameters related to the storage location in question, such as replenishment lead time, customer service level etc.. This approach neglects the interdependence of some variables (such as inventory holding costs and service level) between different stages located at different levels of the distribution network, and for this reason it may bring on unnecessary safety stocks.

Beside the inventory optimization model, some specifications about its implementation should be disclosed.

The existing model has been developed using Microsoft Excel What-if Analysis, being the most appropriate working tool for the project purpose among the available softwares at the moment of the model building. The Excel model is structured in a way, such that the user fills each single required field with an ad-hoc calculated value and activates the model run through the Excel function "what-if analysis – goal seek". The input data entry is carried out manually every time that data change and a that a new model run is required to determine safety stock level. The model run implies a processing time of some hours, given the handled amount of data, and it is carried out for one location at a time. That means, that safety stock allocation is determined not simultaneously for all considered stocking locations (Barilla regional warehouses in practical terms), but the model runs for one single location only at a time.

Given the significant amount of data to handle in the model, the utilization of Microsoft Excel turns out as constraint for different aspects.

First, the model setting is not structured and so not straightforward to follow. Since the user is required to enter manually all input data, the user knowledge and experience about the model is a key element for the correct and complete input data entry. The lack of a standardization of input data entry process can lead to higher risks of errors in the process, and it may also discourage new users' adoption and confidence.

Second, the software storage and computational capacity represents a relevant constraint for the model employment, especially assuming a medium-term perspective with an increasing number of storage locations to monitor and to embed in the optimization model. In practical terms, the current amount of data that the optimization model has to handle, running the what-if analysis functionality, generates relatively long processing time that lower the overall model flexibility.

In summary, the existing safety stock optimization model results to be a correct methodology to determine the level of safety stock at the regional warehouses in Barilla network. Indeed it considers forecast demand and not historical demand, allowing to consider commercial activity effects on demand and other time-related factors that could not be fully included in the past demand pattern. Forecast accuracy is measured through Mean Squared Error (MSE), expressing the variance of forecast from the actual demand. On the other side, replenishment lead time is assumed as a stochastic variable and also its variability is considered in the model. Both demand and lead time are taken as stochastic parameters and so they are taken into account both with their expected values and standard deviations values.

Nonetheless, the existing optimization model shows some critical gaps both in terms of model structure and in terms of implementation. These could represent a starting point for further improvement regarding the safety stock optimization in Barilla regional warehouses, as it will be disclosed in 0 3.

# CHAPTER 3
# OBJECTIVES AND METHODOLOGIES

## 3.1 Project Objective

Safety stock optimization project belongs to a set of supply chain planning initiatives narrowly focused on efficiency-driven objectives. It is consistently part of the company supply chain strategy that aims at achieving higher efficiency levels, minimizing costs and meeting a certain customer service requirement.

The project generates in Barilla Supply Chain Network Design department, a strategic supply chain planning unit focused on the development of optimization projects for Barilla production and distribution network. Specifically, safety stock optimization has a distribution-related scope, while other ongoing optimization projects deal with Barilla production network.

As it will be further explained in section 3.2, the safety stock optimization project arises from operating needs, first. Indeed the application of a new validated optimization model is planned to be a decision support system for Barilla operating distribution planning unit for the allocation of safety stocks throughout the company network.

If the model is proven to fit Barilla distribution and inventory network, and to be implementable in the operating activities related to stock planning and allocation, it is planned to be utilized for a strategic function, besides the operating one. Indeed, Barilla supply chain network design unit expects to utilize the new safety stock optimization model as a network design tool.

Specifically, the strategic unit projects considers the inventory optimization model an additional means, which, integrated to other existing network sourcing optimization models, can be implemented for what-is analysis on Barilla local and global supply chain system. The idea is to have multiple available optimization models that, employed in an integrated way, could monitor the whole company supply chain network and could enable what-if analysis for the allocation of either production or distribution nodes and for the study of production and distribution capacity balance.

The pilot project objective was identified in the application of a multi-echelon safety stock optimization model on Barilla distribution network. Specifically, a first project scope was restricted to Barilla regional warehouses, which are seven in Italy and five in the rest of Europe.

The validation of the model consists in assessing whether a multi-echelon safety stock optimization model may be applied to real Barilla distribution network, whether the model can be consistent with the current operating inventory planning policy and whether it actually bring economic benefits compared to the as-is stock allocation.

Therefore, the project hypothesis to evaluate is that a multi-echelon safety stock optimization developed with Supply Chain Guru on-shelf models, could result an appropriate methodology to integrate in Barilla inventory planning process.

Indeed, the final objective is to enable an integrated process for assessing the optimal level of safety stock in Barilla network, by not restricting the scope to the downstream nodes taken as single entities, but by running a comprehensive optimization analysis on the whole network to determine a safety stock placement that minimizes inventory holding costs and that guarantees a target customer service requirement at the same time.

Moreover, given the high potentialities of the on-shelf optimization software *Supply Chain Guru*, a study on safety stock optimization could achieve surely new findings such as safety stock allocation outputs, given the item demand patterns and parameters related to their flows along the network.

## 3.2 Methodologies

The existing safety stock optimization system, as outlined in section 2.2, is a single-echelon model based on the assumptions that demand and lead times are two independent and stochastic variables. Still, if from one hand the model provides with a structured and scientific method for safety stock allocation based on Hadley and Within formula (substituting historical demand with forecast demand), from the other hand some points related to the model structure and to its implementation are critical.

Specifically, the fact that the existing model is based on a single-echelon system represents a limitation compared to a multi-echelon model that could represent better the real Barilla distribution network, considering the interdependences of some variable performances between the different echelons. A multi-echelon system, indeed, does not allocate the optimal stock level to a single stage, but assuming an holistic supply chain perspective, determines the optimal stock level at each stocking location in the model, with the objective to minimize the overall inventory holding cost and to meet a given customer service level.

With a medium and long-term perspective, the process of safety stock optimization is expected to be carried out in an integrated way for the whole supply chain and this raise the possibility of a multi-echelon safety stock optimization structure.

In order to check whether with a multi-echelon structure implementation, safety stock optimization could result beneficial compared to the actual stock level, a model simulation has been assumed necessary.

The plan for a model simulation implied the definition of the appropriate working tool. The identification process of the model tool has interested both Microsoft Excel and a second on-hand software, Supply Chain Guru.

Supply Chain Guru, as disclosed in-depth in section 0, is an integrated optimization software developed by Llamasoft, Inc.. Recently Barilla supply chain planning department has invested in Supply Chain Guru licence, for carrying out supply chain optimization projects and what-if analysis concerning either production or distribution system capacity. Specifically, Inventory Optimization technology is an optimization model embedded in the software that provides with a structured logic for solving the safety stock allocation problem in a multi-echelon network.

On the other hand, Microsoft Excel provides with ready-to-deploy optimizers, whose computational capacity represents a limitation for the development of complex optimization models.

Given the constraints incurred with the implementation of the existing optimization model in Microsoft Excel, the need to find an alternative, structured and powerful tool combined with the availability of optimization packages to test, lead the supply chain planning unit to select Supply Chain Guru as working tool for testing a new safety stock optimization model.

The preliminary phase that followed the selection of the working tool dealt with a comprehensive and significant study of Supply Chain Guru.

A theoretical virtual manual, provided by the software company, represented a key resource to refer to for the understanding of the software logic and structure. The research was not limited to Llamasoft online guidebook only, but it involved a scientific literature review related to supply chain management and planning. Specifically, the thematic areas that have been covered throughout a scientific literature study mainly dealt with demand categorization and inventory optimization (with a narrow focus on safety stock). Indeed, as it will be described in Chapter 4, Supply Chain Guru integrates a demand analysis phase into the safety stock optimization model for an understanding of demand patterns with the purpose to allocate the optimal stock level consistently with the item-specific demand characteristics.

The scientific literature analysis resulted a key and necessary activity for the software theoretical logic comprehension, providing a knowledge basis regarding demand analysis for stock control policies, in a first phase, and regarding inventory optimization models in a subsequent phase.

A consistent abstract research led to a sufficient mastery of the topics, fundamental for fostering the confidence with the optimization model rationale.

Thus, the process related to the familiarization with the optimization model was initiated with a structured theoretical literature analysis, which put the basis for a second step: the operating experience with the tool.

Also at this stage, the reference to backup material turned out crucial for the understanding of the model tables and their input parameters. Indeed, a daily and constant application to the working tool supported by online practical material, including a guidebook, tutorials and user-forums, contributed to a gradual consistent knowledge about the software optimization model.

Also the exchange and the information sharing with colleagues facilitated the assimilation of some concepts and some software-related competence enrichment.

Moreover, Barilla distribution planning division has been involved into the project, as supporting function providing some relevant information about stocks and distribution network, and contributing to the analysis of the stock optimization model in question, by assuming a strictly operating perspective.

## 3.3 The Working Tool: Supply Chain Guru

*Supply Chain Guru* is an integrated software, developed by Llamasoft for optimizing supply chain networks, transportation routing and safety stock. It also provides simulation functionality. The software can boast multiple strengths that make it very attractive to big companies seeking founded tools for supporting network design and optimization decisions. First, it has a user-friendly interface based on Microsoft Office: Supply Chain Guru tables can be handled using Microsoft Excel, Microsoft Access and Microsoft SQL Server, facilitating the injection of massive amount of data. Second, the software is an integrated platform for running different optimization packages, focusing on different supply chain network areas. The user can generate an optimization model on a network as a whole (optimizing both production and distribution), on transportation routing and on inventory. These optimization packages may apply on the same input project, providing the user with multiple accurate optimized output related to the network under analysis. A certain degree of model flexibility is given by custom constraints regarding production, flow, transportation, storage capacity.

Moreover, the software platform embeds more than one solver able to perform linear and dynamic programming algorithms, that will be further disclosed in section 4.3.4. Among the different software optimization models, Inventory Optimization has been selected for the project purpose, since it responded to the specific project objectives. Inventory optimization includes three different sub-models:

a. *Safety Stock Optimization* aims at defining an optimal level of safety stock over the whole network, utilizing a variant of Guaranteed-service model algorithm developed by Graves and Willems for multi-echelon safety stock optimization problem.
b. *Safety Stock Infeasibility Diagnosis* is used for detecting potential infeasibility causes in running safety stock optimization.
c. *Service Level Optimization* is recommended optimization model to apply on an optimized network (defined by *Safety Stock Optimization*, which generates the safety stock placement), with the objective to optimize the service level for every product at a customer-facing node to reach specific goals, such as profit maximization, cost minimization or achievement of a revenue level target.

Besides, *Safety Stock Optimization* output may be simulated with *Inventory Simulation* technology, which allows to test the performance of optimized policy values, resulted from *Safety Stock Optimization* model.

In the undertaken project *Safety Stock Optimization* model has been implemented, with the support of *Safety Stock Infeasibility Diagnosis* technology to facilitate the identification of infeasibility causes, when infeasibility occurred in the developed model.

# CHAPTER 4
# INVENTORY OPTIMIZATION AND SUPPLY CHAIN GURU

Given that *Supply Chain Guru* represented a powerful tool for a potential optimization project, tackling the level of inventories in the company-owned regional warehouses, the high-level logic behind *Safety Stock Optimization* model represents a draft for the project methodology followed.

The first stage of the model is represented by demand analysis, which provides with relevant demand statistics and with a categorization of input demand according to two variables: intermittency and variability. To run a successful demand analysis the model must be inputted with customer demand data, either in form of historical demand series or of forecast demand. In addition to this, since demand analysis is performed throughout the whole distribution network and it is not restricted only to the most downstream node that serves the final customer, information about supply chain network must be entered for allowing a demand propagation. Indeed, from the customer-facing facility customer demand is propagated backwards based on user-defined network of nodes (physical plants and/or warehouses) and arcs (routes that connect the nodes for the movement of products), so that the software is able to allocate (and subsequently to analyze) demand on each single node. Figure 7 provides a representation of the whole process, identifying the required user-defined input information in red, the model operation in blue and the operation output in green.

Demand analysis outputs represent necessary information for the second main model stage: inventory optimization. The determination of optimal inventory level, distinguished among safety stock, cycle stock and in-transit stock, requires further information about the network and about the target service level guaranteed to the market. Specifically, given the stocking sites of the network, so defining which nodes are eligible for stocking products, the optimization requires replenishment lead time mean value and variability, inventory costs, and the target service level to determine the optimal level of safety stock. Additional *SSO* model output are recommended inventory management policies based on each product demand pattern and statistics relative to lead time demand.

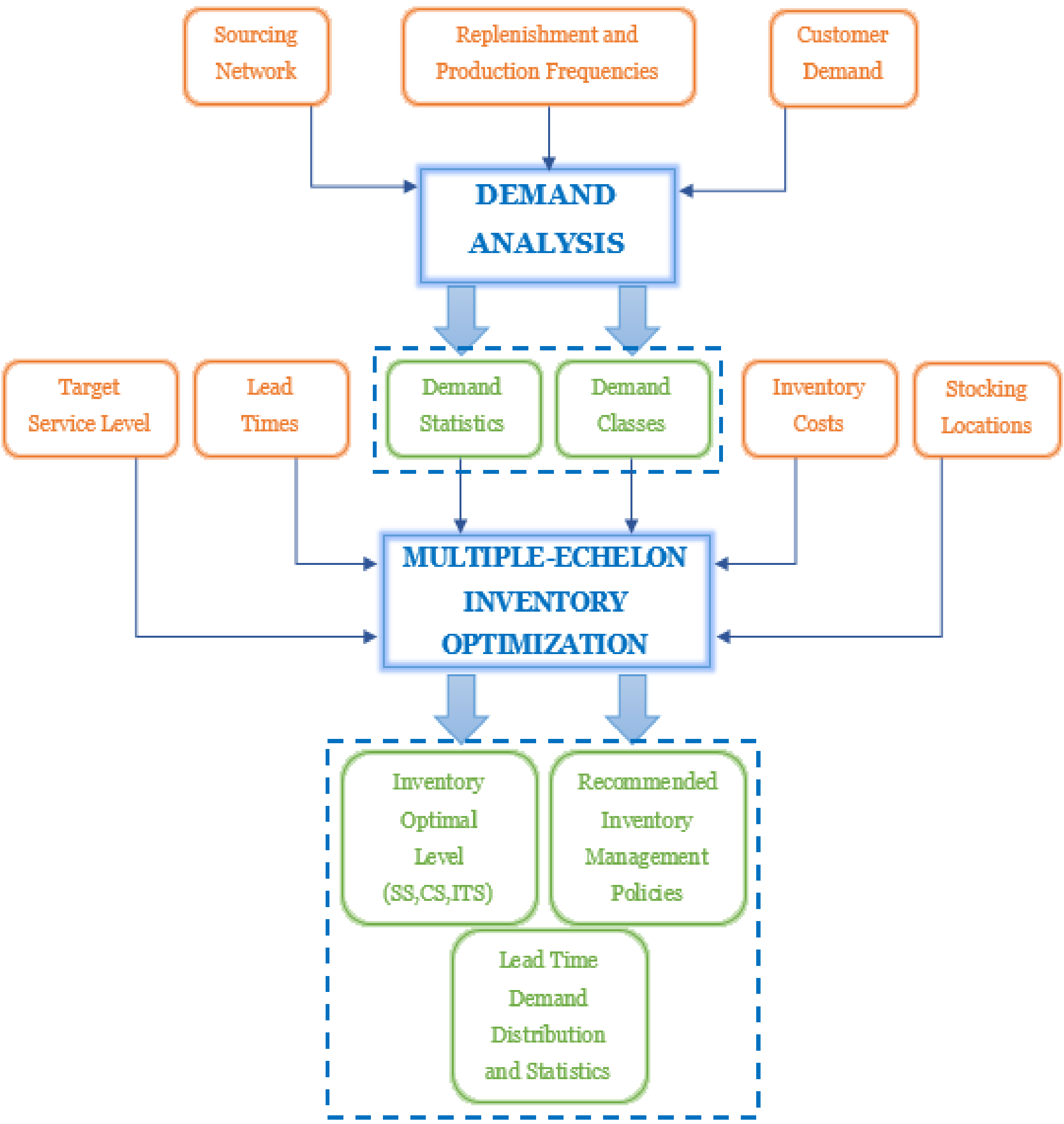



Figure 7: Structure of Safety Stock Optimization model in Supply Chain Guru

The following sections are structured in a specific order, so that initially a general outlook on how an SSO Model can be developed in Supply Chain Guru is given, disclosing which are the necessary input data and where these elements are injected in the optimization model. Given a comprehensive structure of the model, the methodology is deepened by explaining the steps of SSO Model: demand analysis and multi-echelon safety stock optimization.

# 4.1 Building Inventory Optimization Models on SCG

This chapter discloses which are the required input information for an inventory optimization model and how they are embedded in the SCG model. Besides the description of necessary input data, a general structure of SCG input tables will be provided in the following sections.

## 4.1.1 Demand

The most important driver for developing an SSO Model in Supply Chain Guru is customer demand, which can be assumed either as historical or forecasted. Customer Demand Table is the main table where demand series is injected, based on customer-product-date combination. The retrievable information in this table are that a final customer requests a definite quantity of a product on a specific date.

If the demand source is not historical but is forecast-based, demand is entered in User-Defined Customer Demand Profile Table, a specific input table where forecast demand period is defined with mean value and standard deviation of forecast error in a given period of time. The decision concerning the type of forecast error measurement is taken by the user, who may express forecasting error based on his preferences.

Briefly, a set of possible measurements to express forecast error is provided:

- *Mean Absolute Deviation* (MAD) measures the absolute deviation of forecast value from the actual one.

$$MAD = \frac{\sum |D_t - F_t|}{n}$$

- *Mean Absolute Percentage Error* (MAPE) expresses the absolute deviation of forecast value from the actual value as a percentage of the actual demand value.

$$MAPE = \frac{1}{n} \sum \frac{|D_t - F_t|}{D_t}$$

- *Mean Squared Error* (MSE) measures the variance of forecast error.

$$MSE = \frac{1}{n}\sum(D_t - F_t)^2$$

Being not as straightforward and intuitive as other forecast error measurements like MAD and MAPE, Root Mean Squared Error (RMSE) is used to express the standard deviation of forecast error.

$$RMSE = \sqrt[2]{MSE} = \sqrt{\frac{1}{n}\sum(D_t - F_t)^2}$$

### 4.1.2 Products

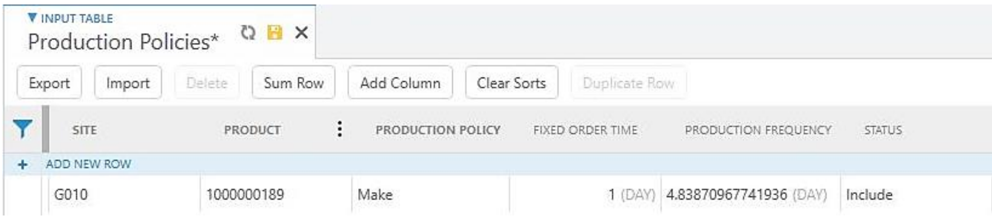
Finished products reported in the demand tables and semi-finished products included in the model are defined in the *Products Table*. In this table a generic product registry may be built with specific information like unit cost, unit price, unit weight, unit volume, product type (discrete or continuous) and shipping class (variable used for LTL transportation mode). The level of detail of product information included in *Products Table* may vary depending on user's needs.

### 4.1.3 Network

This section discloses the adopted methodology to model and frame a production and distribution network given the structure of SSO Model in SCG. Input data are entered among different input tables, namely *Sites Table*, *Customers Table*, *Production Policies Table*, *Site* and *Customer Sourcing Tables* and *Inventory Policies Table*.

*Sites Table* contains all physical nodes included in the model network, regardless their ownership and their position along the supply chain and in the distribution network. Thus, each production plant, co-producer plant, supplier plant, warehouse, are defined in *Sites Table*, if included in the model. In parallel, customers sites are to be defined in the designated *Customers Table* with possible additional information about their site location, their organization and site sourcing policy.

Given the physical nodes of the network, input data about where each product is produced are provided in *Production Policies Table*: for each product requested in the *Customer Demand Table* the model is provided with information about where the given product originates along the network and the corresponding production frequency, expressed as the number of days between two consecutive production cycles of the same product. The production site of a given demanded product, represents the point of origin of the product sourcing flow along the network.

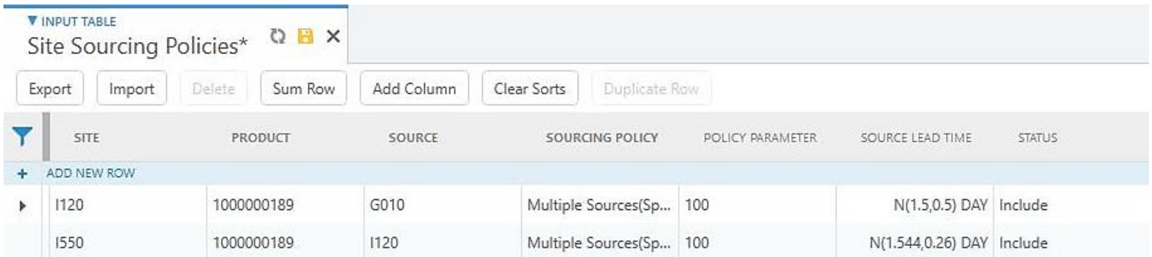

INPUT TABLE
Production Policies*

Export | Import | Delete | Sum Row | Add Column | Clear Sorts | Duplicate Row

| SITE | PRODUCT | PRODUCTION POLICY | FIXED ORDER TIME | PRODUCTION FREQUENCY | STATUS |
|---|---|---|---|---|---|
| G010 | 1000000189 | Make | 1 (DAY) | 4.83870967741936 (DAY) | Include |

Figure 8: Supply Chain Guru Production Policies Table.

The possible sourcing lanes of the distribution network are defined in *Site Sourcing Policies Table*: from its production site, where a given product originates, to the final customer that requested the item, the product is moved along specific routes within the network that must be determined in *Site Sourcing Policies Table*. In this way the model is provided with a fixed production and distribution network structure: given a product that is demanded by the final customer, the model is able to retrace backwards its sourcing network, from the customer-facing node to the corresponding production site. While *Site Sourcing Policies Table* gathers input data about sourcing lanes within the internal network, *Customer Sourcing Policies Table* is another input table showing the sourcing lanes for each demanded product from the customer-facing node to the final customer touchpoint.



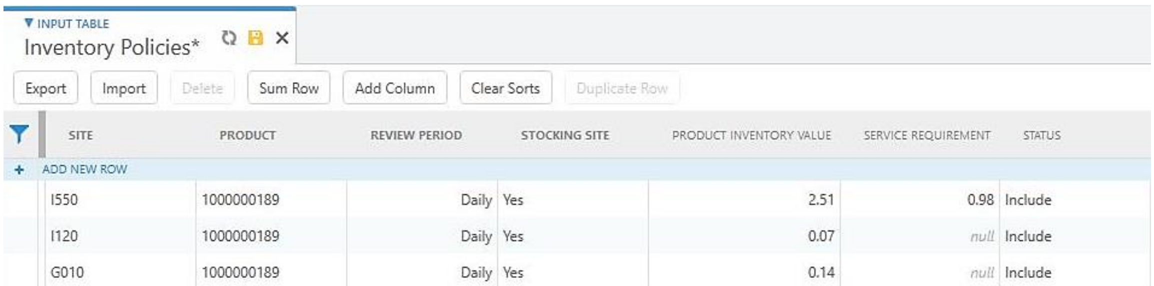
INPUT TABLE
Site Sourcing Policies*

Export | Import | Delete | Sum Row | Add Column | Clear Sorts | Duplicate Row

| SITE | PRODUCT | SOURCE | SOURCING POLICY | POLICY PARAMETER | SOURCE LEAD TIME | STATUS |
|---|---|---|---|---|---|---|
| ADD NEW ROW | | | | | | |
| I120 | 1000000189 | G010 | Multiple Sources(Sp... | 100 | N(1.5,0.5) DAY | Include |
| I550 | 1000000189 | I120 | Multiple Sources(Sp... | 100 | N(1.544,0.26) DAY | Include |

Figure 9: Supply Chain Guru Site Sourcing Policies Table.

Once the distribution network is defined in the model through the methodology described above, the model requires input information about storage policies, specifically defined in *Inventory Policies Table*. The table is structured based on a period-site-product combination, so that each table line expresses that a given node handles a specific item, since the site can be either the production site of the given item (as prescribed in *Production Policies Table*) or a warehouse where the item is temporarily stocked to reach the final customer (as prescribed in *Site Sourcing Policies Table*). The considered node can be entered as "stocking site", where the given product may be physically stored. Indeed, any "stocking site" among the existing sites in the model is eligible for having stocks of the product in consideration.



INPUT TABLE
Inventory Policies*

Export | Import | Delete | Sum Row | Add Column | Clear Sorts | Duplicate Row

| SITE | PRODUCT | REVIEW PERIOD | STOCKING SITE | PRODUCT INVENTORY VALUE | SERVICE REQUIREMENT | STATUS |
|---|---|---|---|---|---|---|
| ADD NEW ROW | | | | | | |
| I550 | 1000000189 | Daily | Yes | 2.51 | 0.98 | Include |
| I120 | 1000000189 | Daily | Yes | 0.07 | null | Include |
| G010 | 1000000189 | Daily | Yes | 0.14 | null | Include |

Figure 10: Supply Chain Guru Inventory Policies Table.

Figure 11 is a simplified network representation composed of three nodes, covering three different roles (production plant, warehouse and customer delivery location) and linked through a blue and a green arrow, which prescribe the movement of products along the network. The grey dotted lines connect the physical and real network elements to the corresponding SCG input tables where these elements are entered in a general SSO model.

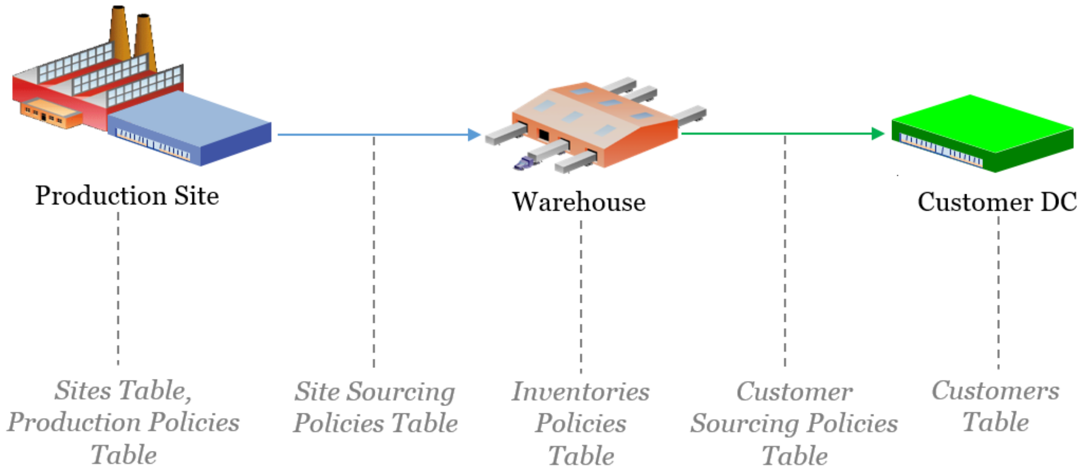



Figure 11: Building a Network with Supply Chain Guru Input Tables

### 4.1.4 Lead Times

Lead time values are necessary input information for determining the optimal level of safety stock to buffer against demand and replenishment lead time variability. Being lead time of a stage the time-length of a process performed at that stage, given that all input items are available to start the process, the same concept entails different activities run during this time-window. In *Supply Chain Guru*, and specifically in an SSO model, replenishment lead time does not assume a single value and expression, but it is broken down into multiple lead time parts, related to the different activities occurring in a general replenishment lead time.

Consider a site $i$ in a general network, where $i$ represents a stocking node and a non-production node for a given product $x$. Based on a static and defined sourcing network, product $x$ is replenished in site $i$ from an upstream site $j$. Based on these assumptions, *Supply Chain Guru* assumes a *Sourcing Lead Time*, as the amount of time needed for site $j$ to prepare the order for replenishing site $i$ of product $x$. *Sourcing Lead Time* starts with the replenishment order receipt and finishes when the order is ready to be shipped. It is entered in *Supply Chain Guru* on a sourcing lane basis and also based on ordered product in the specific input table *Site Sourcing Policies Table*, where the sourcing lanes are defined in the model. Namely, *Sourcing Lead Time* field may be populated with a discrete number value or alternatively as a Gaussian normal distribution, expressed as $N(\mu,\sigma)$.

*Transportation Lead Time* is the second lead time component that follows sourcing lead time from a conceptual point of view. Indeed, it represents the amount of transportation time needed to replenish the destination site. Thus, recalling the previous example, product $x$ takes a positive transportation lead time from the moment the order is available in site $j$ for the shipment and the moment it is received by the downstream site $i$. Since it is a value affected by distance and transportation mode, which depend on the specific lane, *Transportation Lead Time* can be expressed based on the possible transportation routes within the network defined in the model in *Supply Chain Guru*. Specifically in *Supply Chain Guru,* the input table *Transportation Policies Table* is populated by the user with all possible transportation lanes for any demanded product and for every transportation lane a *Transportation Lead Time* value is entered in form of a discrete value or of a Gaussian normal distribution $N(\mu,\sigma)$, to express its average value and its variability.

Besides, in every stocking site defined in the model there will be an inventory review frequency that expresses how often available inventory level is controlled to assess whether an order of a demanded product is required to fulfil a downstream order (that, in case of a multi-echelon network, could be the final customer order in a customer-facing site or a an order issued by a downstream node). This information is embedded in the concept of *Review Period* in Supply Chain Guru, specifically entered in the *Inventory Policies Table*. It can assume hourly, daily, weekly, monthly values or alternatively it can be *"continuous"*, meaning that inventory level is reviewed every time a new order is received at the stocking site.

In production plants the stock replenishment of a given product does not imply any inter-site flows, but it is fulfilled by in-site production. The fixed production time of product $x$ occurred in site $j$ it is expressed as Fixed Order Time in Supply

Chain Guru. It is a fixed time, since it is determined regardless the production quantity of the considered product. Table 2 reports the lead times defined in Supply Chain Guru and the corresponding input tables of SSO Model where the lead time values are entered by the user.

| ***SSO Model Input Tables*** | ***Lead Time Components*** |
| --- | --- |
| Site Sourcing Policies Table | Site Sourcing Lead Time |
| Customer Sourcing Policies Table | Customer Sourcing Lead Time |
| Production Policies Table | Fixed Order Time |
| Transportation Policies Table | Transportation Lead Time |
| Inventory Policies Table | Inventory Review Period |

Table 2: Lead time components in Supply Chain Guru tables

Once the multiple components of replenishment lead time in *Supply Chain Guru* have been disclosed, it is possible to introduce briefly how the total replenishment lead time is built during the optimization.

Two distinct types of *Immediate Lead Time* are built up by the optimization software: for those stocking sites that coincide with the production location of a given product, *ILT* (*Immediate Lead Time*) is the sum of *Fixed Order Time* (fixed production time of the product, regardless its production quantity) and *Inventory Review Period*. Indeed, the replenishment is carried out without the need of external sourcing, since the product is produced in the same node. Differently, for those nodes that are stocking sites only for a given product, ILT is given by the sum of *Sourcing Lead Time*, *Transportation Lead Time* and *Review Period*. Sourcing and *Transportation Lead Times* are values that are affected by the sourcing network and so by the sites' couple (the upstream node that is called for fulfilling the replenishment and downstream node that receives the replenishment), while *Review Period* is determined by the downstream site only.

Recalling the previous example, where site $i$ is the downstream node that requests a replenishment of product $x$ to site $j$, Immediate Lead Times of the different stocking sites may be written as follows:

$$ILT_{j,i} = Sourcing\ LT_{j,i} + Transportation\ LT_{j,i} + Review\ Period_i$$

$$ILT_j = Fixed\ Order\ Time_j + \ Review\ Period_j$$

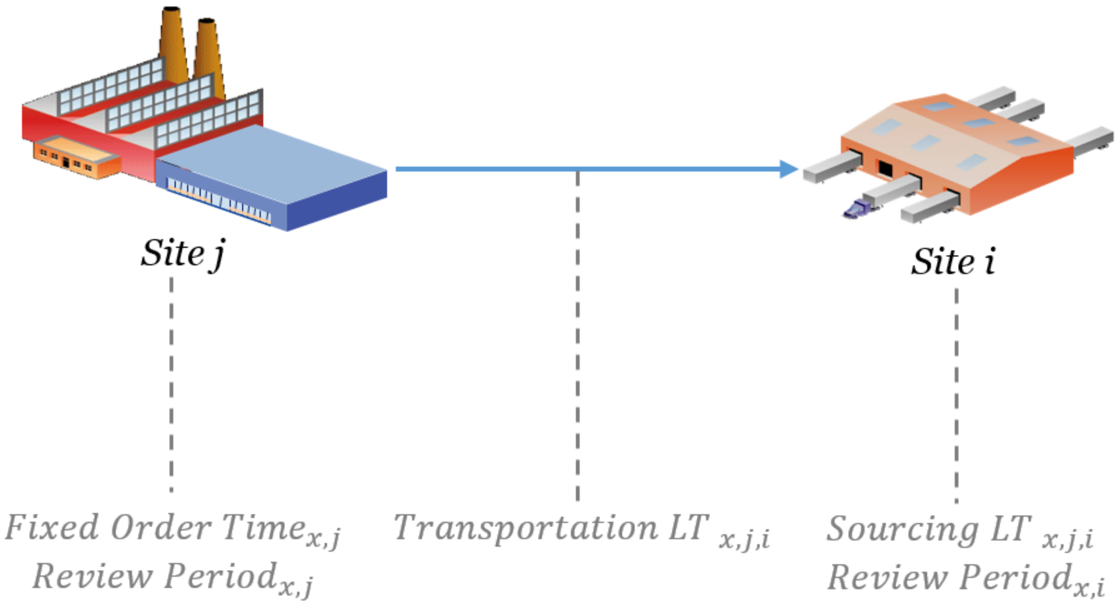



Figure 12: Replenishment Lead Time in Supply Chain Guru

### 4.1.5 Inventory Holding Costs

The optimal safety stock level to protect against demand and replenishment lead time variability is determined to guarantee a specific service level minimizing the overall cost. This implies that the model must be provided with data about inventory costs.

The economic value of inventory may be expressed as input datum in two different possible fields: *Product Value*, expressing the unitary economic value of a product regardless its stocking location along the network, or alternatively *Inventory Product Value,* which assumes a product monetary value varying according to the stocking site where it is placed. In other words, *Inventory Product Value* embeds different economic components or inventory that depend on the storage site, such as unitary handling costs or unit storage cost. *Inventory Product Value* is a field of *Inventory Policies Table*, which reports that a given site of the network is a stocking site for a specific product, at a precise cost (expressed through *Inventory Product Value*). *Product Value* is a field in *Product Table*.

Thus, in order to express the inventory value that actually varies according to the stocking site where the product is located, *Inventory Product Value* field is preferred. Which inventory cost component to include in *Inventory Product Value* is a user's decision.

The fact that *Inventory Product Value* or *Product Value* are the only input monetary values necessary for the optimization objective function lies on the assumption that supply chain network is fixed through defined sourcing, inventory and transportation policies entered in the corresponding model input tables. Being transportation routes and modes static for every inter-site movement of goods, there is no option for exceptional transportation policy associated to an additional cost. Transportation costs do not impact directly in the inventory optimization, but only the cost components that are embedded in *Inventory Product Value* are included in the objective function of the model optimization.

### 4.1.6 Service Level

*Service Requirement* presents the target service level that the stocking site (in a given period and for a given item) must guarantee to its downstream sites, regardless they are either customers or internal nodes.

Service level can be determined as a relation of the number of time periods that accept stock shortages and the total number of considered periods, or alternatively as the admitted probability of shortage occurrence. SCG supports four different service measurements to express service level in the model, which are listed and further disclosed below:

- Probability of not Stocking Out
- Quantity Fill Rate or Item Fill Rate
- Undershoot
- Ready Rate

Probability to avoid stock out method is based on the assumption that demand during lead time is normally distributed with mean $ED_{LT}$ and standard deviation $\sigma_{DLT}$.

Given Order Point $OP$, and the coefficient of the expected service level $k$, the probability to avoid stock out $PSO$ is expressed with the following formula:

$$PSO = P(D_{LT} < OP) = P(D_{LT} - ED_{LT} < SS) = P\left(\frac{D_{LT} - ED_{LT}}{\sigma_{LT}} < k\right) = P(z < k)$$

With $z$ being standard normal distribution with mean equal to 0 and standard deviation equal to 1.

The second supported service measurement, Fill rate, is an indicator measuring the capability to meet customers' requests through inventory on hand. Item fill rate is a fill rate at item/SKU level and can be expressed through the following formula:

$$IFR = 1 - \frac{Expected\ Shortage\ in\ a\ Cycle}{Expected\ Demand\ during\ a\ Cycle}$$

A replenishment cycle corresponds to the lead time starting with the arrival of replenishment order quantity Q and ending with the consumption of the same quantity. The expected shortage at the end of replenishment lead time $ESC_e$ can be expressed as:

$$ESC_e = -(ROP - \mu_{LTD}) \times \left\{1 - normdist\left(\frac{ROP - \mu_{LTD}}{\sigma_{LTD}}\right)\right\} + normdist\left(\frac{ROP - \mu_{LTD}}{\sigma_{LTD}}\right) \times \sigma_{LTD}$$

Where $ROP$ represents the reorder point quantity and $\mu_{LTD}$ and $\sigma_{LTD}$ stand for respectively mean and standard deviation of lead time demand.

As we will see in 0, Item Fill Rate is the service measurement selected for expressing service level in the SSO Model developed in Barilla, since it is a currently accepted and utilized indicator for company performance measurement.

Undershoot is the third service measurement available in a SSO model in SCG. Namely, undershoot is defined as the amount of inventory below the reorder point. Basically, this method assumes that the replenishment lead time beginning corresponds to an Inventory Position (IP) below the reorder point by the undershoot value. Thus, when considering the presence of undershoot, the reorder point should be enough high to cover the demand during the replenishment lead time and undershoot. The adjusted lead time demand mean and the adjusted lead time demand variance, respectively $\mu_{LTD}^*$ and $\sigma_{LTD}^*$ are expressed as follows:

$$\mu_{LTD}^* = \mu_{LTD} + Undershoot\ Mean$$

$$\sigma_{LTD}^* = \sigma_{LTD} + Undershoot\ Variance$$

Moreover, the service indicator (Undershoot) is formulated as:

$$U = \frac{(ESC_e - ESC_b)}{Q}$$

Where $ESC_e$ and $ESC_b$ are the expected shortage respectively at the end and at the beginning of a replenishment cycle. $Q$ is the replenishment order quantity. Undershoot ($U$) adjusts the expected shortage during a cycle according to the magnitude of the replenishment order ($Q$).

Ready rate is another indicator to express service level. Specifically, it is defined as the fraction of time when the net inventory is positive (Silver et al., 1998), meaning that the rate represents the portion of demand periods, in which demand is immediately served because of sufficient on-hand inventory. Ready-rate ($RR$) is calculated as follows:

$$RR = 1 - \frac{N_{stockout}}{N_{total}}$$

Where $N_{stockout}$ corresponds to the number of time buckets with stockouts, and $N_{total}$ is the total number of time buckets.

## 4.2 First Stage: Demand Analysis

The initial step of the model implies demand analysis with the objective to formulate profiles of each product demand variability throughout the network, a classification for the demand, and other advanced statistics useful to comprehend the demand. Classic techniques and theories concerning safety stock calculation assume a normal distribution of demand and supply. Actually, most demand is not normal, but it has a certain variability level and is not homogenously distributed along different time periods.

*Supply Chain Guru* is powered with *Adaptive Intelligent Inventory Optimization* (AI+IO) technology, a Llamasoft algorithm for demand classification that gives the possibility to analyse and classify product demands, with the purpose to take decisions regarding stocks and inventory policies based on a highly segmented supply chain perspective.

*Safety Stock Optimization* model starts with an analysis of inputted demand that carries out two consecutive functions:

*a.* Demand Characterization
*b.* Demand Classification

### 4.2.1 Demand Characterization

Demand is initially studied for the formulation of demand statistics. Demand characterization implies four progressive steps, which are further disclosed in the next sections.

a. Demand Aggregation
b. Demand Propagation
c. Statistics Formulation
d. Outlier Analysis

## *Demand Aggregation*

In the first phase, site demand is an aggregated of many customers' demand flows allocated to one or more downstream sites during a certain time bucket. The number of demand flows that is allocated to a site and the aggregation time bucket affect the aggregated demand statistics and the related risk pooling effect.

Indeed, the longer time bucket, the greater demand flow number allocated to a site and the higher risk pooling effect. Eventually, the higher risk pooling effect, the lower the relative safety stock level. The aggregation of demand for the analysis is a user-defined option.

The available aggregation period options are three in the model:

*a.* Day – Excluding weekend days and non-work days, demand series are aggregated at daily basis.
*b.* Week – Demand analysis gathers data from all days in a week (from Sunday to Saturday), excluding non-work days and generating an aggregated weekly demand.
*c.* Month – Demand is aggregated monthly, combining demand data from all working days in a month, based on the calendar.

## *Demand Propagation*

Aggregated demand is propagated to all nodes in the distribution network for determining every site demand profile. First, a fixed sourcing and production network must be clearly defined in the software, through *Production Policies Table* and *Sourcing Policies Tables*, so that customer demand can be correctly propagated upstream from the downstream units.

Two methods are available to perform the demand propagation and the user is given the choice to select one of them according to the inputted demand information. The methods are the following:

- **Demand Series Propagation**. This approach does not estimate demand of upstream sites using a formula propagation, but it simply derives site demand given the demand series in *Customer Demand Table*. The methodology provides robust and accurate results, preventing the accumulation of errors with the purpose to calculate demand statistics at site level. The implementation of demand series propagation is feasible on all types of demand, regardless its intermittency and size. Nonetheless, a demand series is strictly required to run demand series propagation and the running time is proportional to demand size.

Demand series Propagation and Formula-based Propagation methods share the same assumption that continuous inventory review policy is assumed to exist in every site of the network.

A very simplified example follows, to disclose the basic implementation of demand-series propagation method. Assume a fixed distribution network, showed in Figure 13, composed of two customers (CZ1 and CZ2), served respectively by two regional warehouses (RW1 and RW2). A single production plant (PP1) replenishes both regional warehouses.

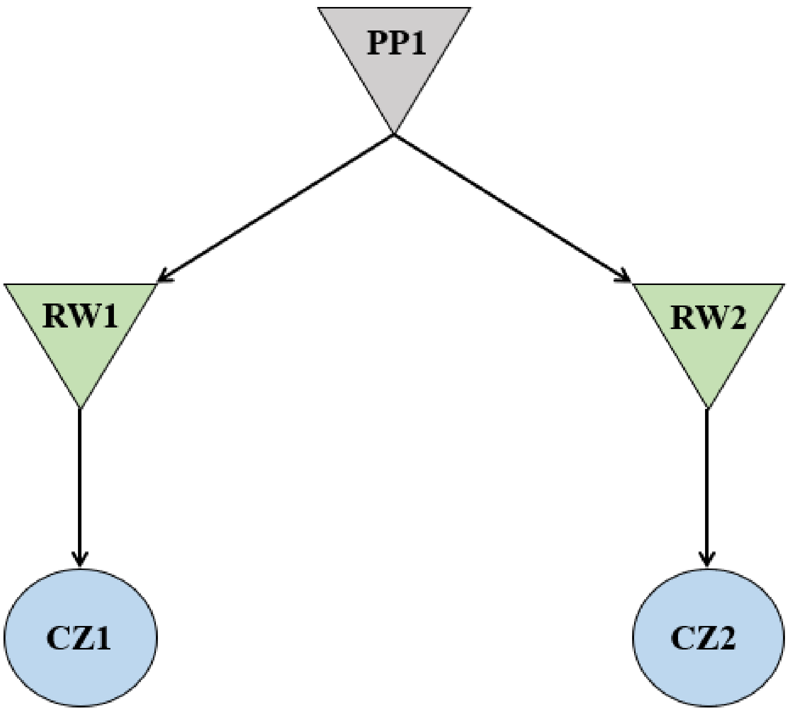



Figure 13: Demand Series Propagation Example

Customer demand series is showed in the Table 3:

| Site | Product | Order Time | Order Quantity |
|---|---|---|---|
| CZ1 | PRODUCT A | 2/01/2018 | 2 |
| CZ2 | PRODUCT A | 2/01/2018 | 2 |
| CZ1 | PRODUCT A | 3/01/2018 | 4 |
| CZ2 | PRODUCT A | 5/01/2018 | 6 |
| CZ2 | PRODUCT A | 6/01/2018 | 2 |
| CZ1 | PRODUCT A | 6/01/2018 | 7 |
| CZ1 | PRODUCT A | 8/01/2018 | 1 |
| CZ2 | PRODUCT A | 8/01/2018 | 5 |

Table 3: Demand Series Propagation Example

Orders issued by the regional warehouses RW1 and RW2 reflect customer demands. Specifically, the production plant PP1 receives the following order series, noting that orders placed at PP1 of the same product on the same day are summed up.

| Sourcing Site | Product | Order Time | Order Quantity |
|---|---|---|---|
| PP1 | PRODUCT A | 1/01/2018 | 0 |
| PP1 | PRODUCT A | 2/01/2018 | 4 |
| PP1 | PRODUCT A | 3/01/2018 | 4 |
| PP1 | PRODUCT A | 4/01/2018 | 0 |
| PP1 | PRODUCT A | 5/01/2018 | 6 |
| PP1 | PRODUCT A | 6/01/2018 | 9 |
| PP1 | PRODUCT A | 7/01/2018 | 0 |
| PP1 | PRODUCT A | 8/01/2018 | 6 |

Table 4: Demand Series Propagation Example

Demand series of PP1 is used to calculate demand statistics:

| **Site** | PP1 |
|---|---|
| **Product** | PRODUCT A |
| **Demand Mean** | 3,625 |
| **Demand Standard Deviation** | 3,378 |
| **Non-Zero Demand Mean** | 5,8 |
| **Non-Zero Demand Standard Deviation** | 2,049 |
| **Inter-Demand Interval Mean** | 1,4 |

Table 5: Demand Series Propagation Example

Inter-demand interval, knows also as ADI (Average Demand Interval), can be calculated as the ratio between the summation of intervals between non-zero demand periods and the summation of non-zero demand periods. ADI formula is expressed as follows:

$$ADI = \frac{\sum_{i=1}^{N} \tau_i}{N}$$

Where $\tau_i$is the interval between two consecutive non-zero demands and $N$ is the occurrence of non-zero demand along the time series.

The example is reported to provide a basic idea about how demand, provided at customer-level and on series-basis, may be propagated along a network, from the downstream unit to the upstream units.

- **Formula Propagation.** The alternative method for demand propagation aims at allocating demand at each site of the network, starting from customer demand acceptable statistics. While demand-series propagation method deals with demand series, this approach is used when demand series is not available and so demand is allocated based on customer demand statistics. Formula propagation is typically used with forecast demand data, which usually are not expressed in series but in statistical values. Advantages related to this method are mainly related to the fact that at operational level, it can propagate demand with no need of an historical series, resulting appropriate for forecast demand. Moreover, its running time is independent from demand size. On the other hand, some critical issues might arise implementing formula propagation method. First, to handle extremely slow-moving items in the demand is impossible using this approach. Moreover, the accumulation of errors represents a relevant problem, since propagation is based on statistical values that are already approximations and so the propagated demand at upstream levels might yield significant errors.

To comprehend more the logic behind formula-based propagation approach, a simplified example, similar as the one used for demand-series propagation, is presented below. A fixed network is assumed to have a single production site (PP1) that replenishes two customer-facing sites (RW1 and RW2) with product A. RW2 specifically serves two customers, facing with different demands. The network structure is represented in Figure 14.

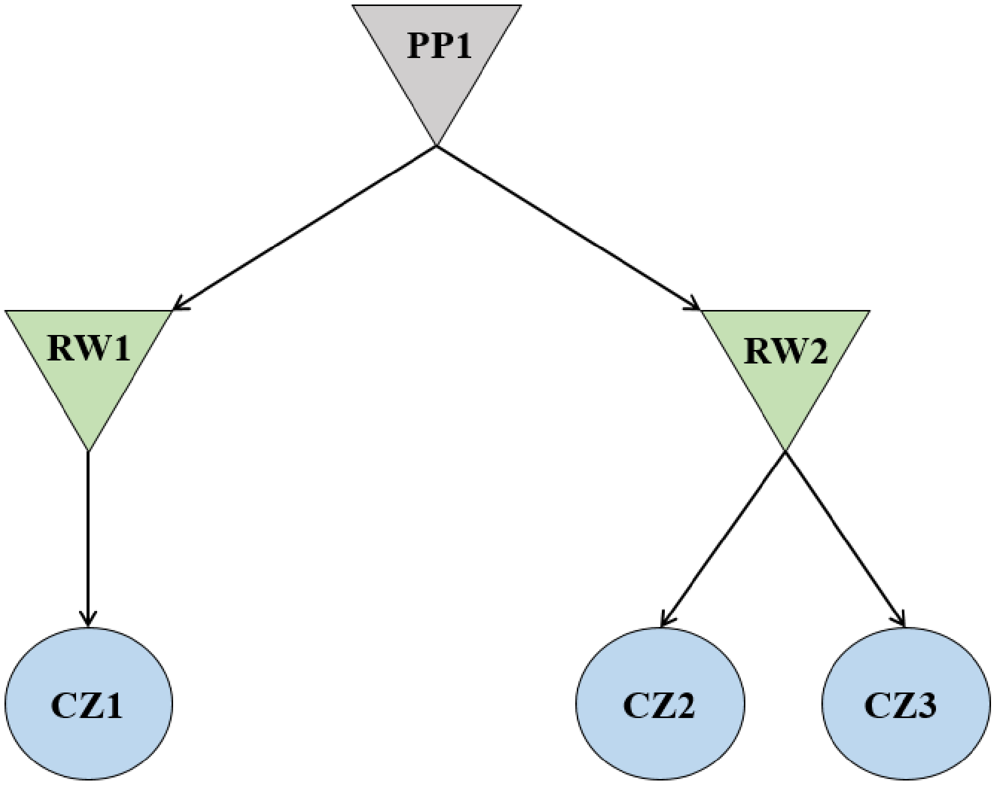



Figure 14: Demand Formula Propagation Example

Input data about customer demand are available not as historical series, but with statistical values, as showed in Table 6.

| Node | Demand Mean μ | Demand Standard Deviation σ |
|---|---|---|
| CZ1 | 160 | 40 |
| CZ2 | 230 | 62 |
| CZ3 | 144 | 58 |

Table 6: Demand Formula propagation Example

Given input demand mean and standard deviation values, formula-based propagation is implemented to generate the site demand statistics, as follows:

RW1 Demand Mean $\mu_{RW1}$ and Standard Deviation $\sigma_{RW1}$:

$$\mu_{RW1} = \mu_{CZ1}$$

$$\sigma_{RW1} = \sigma_{CZ1}$$

RW2 Demand Mean $\mu_{RW2}$ and Standard Deviation $\sigma_{RW2}$:

$$\mu_{RW2} = \mu_{CZ2} + \mu_{CZ3}$$

$$\sigma_{RW2} = \sqrt[2]{\sigma_{CZ2}^2 + \sigma_{CZ3}^2}$$

PP1 Demand Mean $\mu_{PP1}$ and Standard Deviation $\sigma_{PP1}$:

$$\mu_{PP1} = \mu_{RW1} + \mu_{RW2}$$

$$\sigma_{PP1} = \sqrt[2]{\sigma_{RW1}^2 + \sigma_{RW2}^2}$$

With these formulas, demand site statistics are calculated:

| Node | Demand Mean μ | Demand Standard Deviation σ |
|---|---|---|
| RW1 | 160 | 40 |
| RW2 | 374 | 84.9 |
| PP1 | 534 | 93.9 |

Figure 15: Demand Formula Propagation Example

Formula-based propagation method, although it favors the risk pooling effect dealing with statistical values, is appropriate for analyzing forecasted demand data, typically expressed in average numbers. In this case forecasted demand information are entered in the specific input demand *User-defined Site Forecast Profile Table* and formula propagation method is selected in the demand analysis.

### *Outlier Analysis*

Running demand analysis potential outliers are detected through thresholds represented by non-zero demand standard deviation and non-zero demand mean values. Respectively non-zero demand mean $\mu_{NZ}$ is computed as the average demand size during the period at the given site, excluding zero demand records that occur in time series. Similarly, non-zero standard deviation $\sigma_{NZ}$ is the standard deviation of demand size during the period at the given site, excluding zero demand records of the considered time series. Thus, for every site $j$ where demand of item $i$ is allocated, non-zero demand mean and standard deviation are computed respectively with the following formulas:

$$\mu_{NZ} = \frac{\sum_{i=1}^{N} Demand_{i,j}}{N_{NZ} - 1}$$

$$\sigma_{NZ} = \sqrt{\frac{\sum_{i=1}^{N} (Demand_{i,j} - \mu_{NZ})^2}{N_{NZ} - 1}}$$

Outlier analysis is triggered through non-zero standard deviation: if $\sigma_{NZ} \geq 10$, outlier analysis starts.

An outlier $D_{max}$ in a given aggregation period is detected if $D_{max}$ is equal to or greater than ten times the non-zero demand mean from the rest of demand smaller than $D_{max}$.

If $D_{max} \geq 10 * \overline{D}_{NZ,i}$, $D_{max}$ , where $\overline{D}_{NZ,i}$ is non-zero demand allocated to site $i$, excluding $D_{max}$, $D_{max}$ is determined as outlier by the software.

As the outlier is identified, a user-defined model option determines whether:

a. Outliers are still included in demand statistics.
b. Outliers are substituted with non-zero demand mean $\overline{D}_{NZ,i}$ computed with demand data smaller than the outlier $D_{max}$. Outliers are therefore excluded from demand statistics, since adjusted demand is generated.

## 4.2.2 Demand Classification

Following demand characterization, demand classification is the process that clusters demanded items into demand categories with the purpose to identify the optimal demand forecasting method and inventory control policy for each item. In literature many different demand categorization approaches exist and they can be grouped mainly in the following macro-areas:

- Approaches based on variance partition (Williams 1984)
- Approaches based on characteristics of demand shape (Bartezzaghi et al. 1999, Zotteri, 2000)
- Approaches based on forecasting accuracy.

It is important to remark that *AI+IO* demand classification method implemented in *Safety Stock Optimization* model relies on the scientific studies of Syntetos et al. (2015) for approaches based on the accuracy of forecasting procedure. Nonetheless each approach will be briefly disclosed, with the purpose to enhance the key characteristics and the key differences with the demand classification method utilized in the model.

Approaches based on variance partition are based on Williams contribution that developed a categorization method that divides demand variance during lead time $var(DDLT)$ into causal parts as the following: (1) the number of customer orders occurring in consequent units of time having mean $n$ and variance $var(n)$; (2) the order sizes, having mean x and variance $var(x)$; (3) the lead time, having mean $L$ and variance $var(L)$.

Given that (1), (2) and (3) are assumed to be independent and identically distributed random variables, demand variance is described by the following equation:

$$var(DDLT) = x^2 L\ var(n) + nL\ var(x) +\ n^2 x^2 var(L)$$

By expressing $var(DDLT)$ formula with squared coefficient of variation $CV_{DDLT}^2$, it results as

$$CV_{DDLT}^2 = \frac{CV_n^2}{L} + \frac{CV_x^2}{nL} + CV_L^2$$

The sizes of three terms $\frac{CV_n^2}{L}, \frac{CV_x^2}{nL}, CV_L^2$ composing the squared coefficient of variation of demand during lead time are used as variables to define different demand pattern categories. According to authors Williams and Eaves and Kingsman, the specific variable thresholds used to define categories vary depending on the market sector and item type.

Approaches based on demand shape characteristics have been investigated by Bartezzaghi and Zotteri. The authors analyzed demand intermittency proposing two dimensions of demand distribution:

- Demand distribution asymmetry calculated as the third standardized moment of probability distribution;
- The multimodality distribution, or coexistence of more than one mode.

The study carried out by the authors demonstrated that the higher the right asymmetry of demand distribution, the higher intermittence in the demand and so the higher stock level to guarantee a given service level. Despite the authors' achieved results, no categorization on demand patterns has been provided.

The third macro-method in demand categorization literature may be defined as approaches based on forecasting accuracy procedure. This methodology considers intermittency as key dimension in demand analysis. Intermittent demand appears sporadically, with some time periods showing no demand at all. Moreover, when demand occurs, it may not be for a single unit or a constant size (Syntetos and Boylan, 2005).

Croston developed the first intermittent demand specific method, based on inter-demand interval ($p_t$) and demand size, when demand occurs ($z_t$). The author assumes that demand sizes follow the normal distribution (with mean $\mu$ and variance $\sigma^2$) and that therefore inter-demand intervals are geometrically distributed (with mean $p$).

Syntetos and Boylan demonstrated that Croston's estimator was biased and proposed an adjustment factor to make Croston method unbiased.

Syntetos et al. suggests a demand categorization approach based on three methods of scientific literature: (a) Croston's method, designed specifically to forecast intermittent demand, (b) a correction of Croston's estimator, developed by Syntetos and Boylan and (c) simple exponential smoothing (SES).

Syntetos et al. method assesses demand categories through the comparison of MSE computed from each considered method to assess areas of higher accuracy. Intermittency and variability are the demand parameters for classifying demand patterns. Specifically, as shown in Figure 16, the two-axis matrix based on the squared coefficient of variation of demand size ($CV^2$) and the average inter-demand interval ($p_t$), outlines four demand categories: *erratic*, *lumpy*, *smooth* and *intermittent* (but not very erratic), delimited by cutoff values for the two demand categorization variables, determined by Syntetos and Boylan' study.

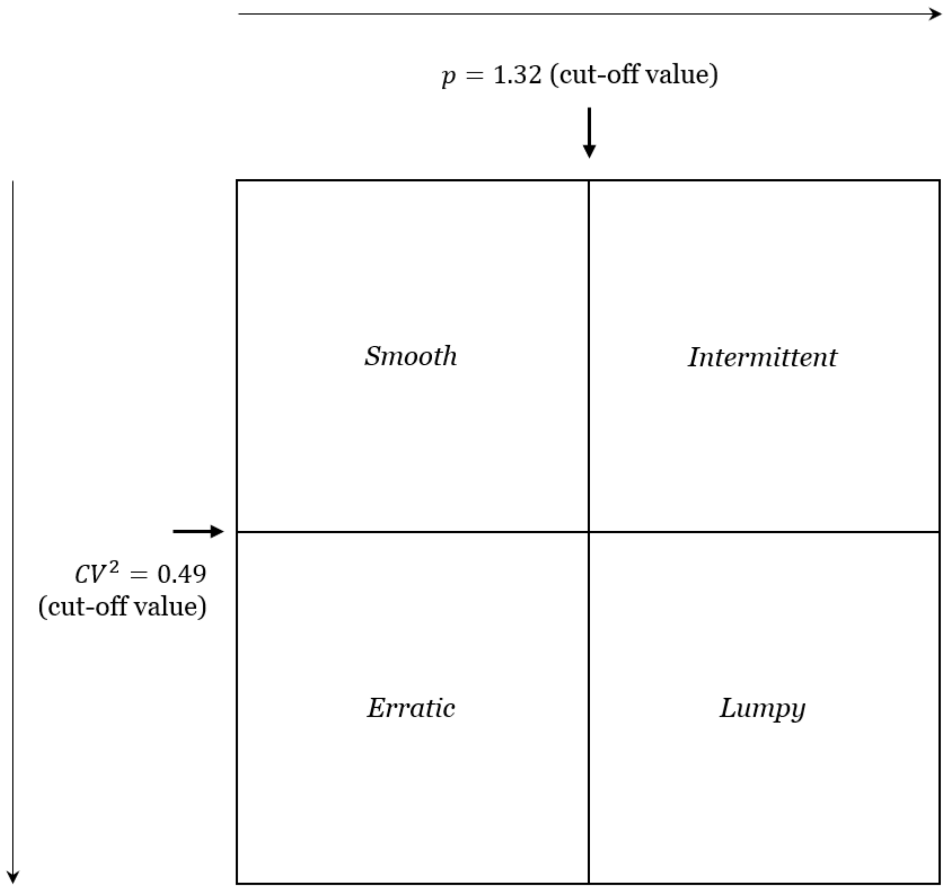



Figure 16: Demand categorization matrix developed by Syntetos and Boylan.

If $p \geq 1.32$ demand is said to be *lumpy*, when $CV^2 \geq 0.49$ and *intermittent* when $CV^2 < 0.49$. Indeed, a demand with a relatively low occurrence during a given aggregation period, is further classified as *lumpy*, if it is highly variable in terms of quantity, or *intermittent*, if quantity remains relatively steady, based on $CV^2$cut-off value defined by the authors.

Differently, given that $p < 1.32$ demand is said to be *erratic*, when $CV^2 \geq 0.49$ and *smooth* when $CV^2 < 0.49$. The left-handed quadrants of the matrix represent, therefore, non-intermittent demand, further distinguished in *erratic* and *smooth* respectively if demand quantity variability is high and low, given the $CV^2$cut-off value defined by the authors.

Syntetos and Boylan' cut-off values for demand categorization variables make the theoretical schema an operational method for demand classification, implemented in *Supply Chain Guru* in inventory optimization models. Figure 17 represents a flow chart that specifically shows the process of demand classification in the software.

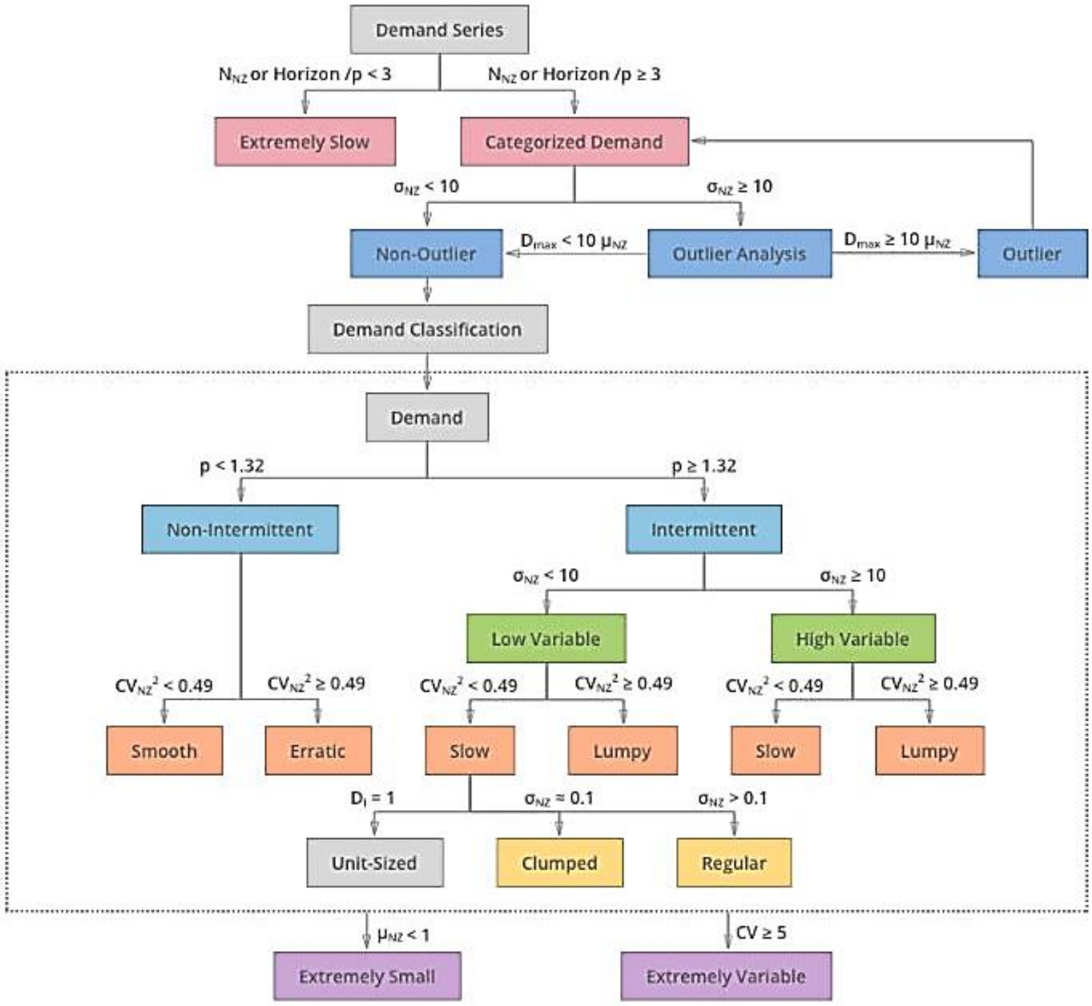



Figure 17: Demand Classification Flow Chart. Supply Chain Guru ® Documentation

Starting from the first column of Figure 17, initially demand is categorized in terms of frequency: if demand occurs less than three times in a given period, it is defined as *Extremely Slow* and no demand statistics formulation is performed. The primary requirement for triggering demand characterization is that demand occurs at least three times in a period. Extremely slow-moving items are excluded from safety stock optimization, since they do not reach a minimum demand occurrence level that justifies physical safety stock levels.

Throughout demand characterization process, demand propagation, statistics formulation and outlier analysis are performed, and after that demand classification starts.

First, demand intermittency is studied with the measurement of mean inter-demand interval ($p$). The cut-off value determined by Syntetos and Boylan for this parameter is utilized to distinguish intermittent demand from non-intermittent demand. Following non-intermittent demand path, demanded items are classified as *Erratic* if their demand results highly variable and as *Smooth* if their demand results stationary. Squared coefficient of demand variation ($CV^2$) is the variable utilized to define *Erratic* and *Smooth* demand classes.

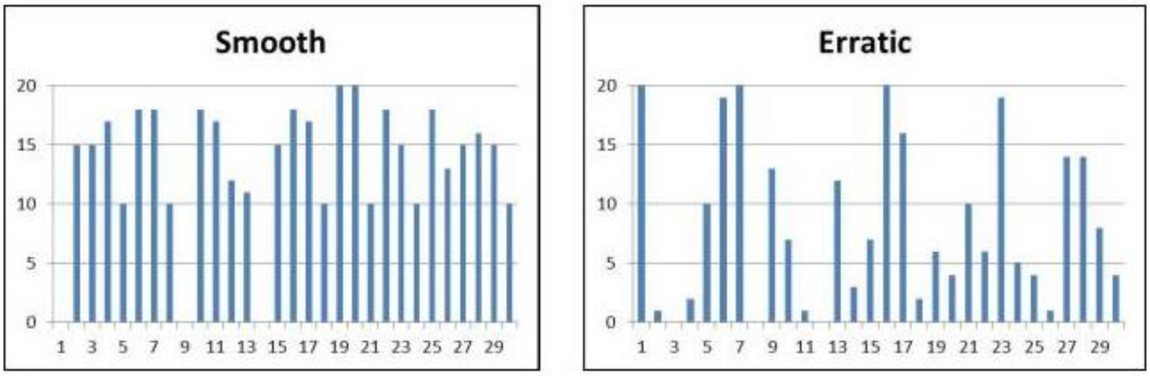



Figure 18: Graphical representation of smooth and erratic demand patterns. Supply Chain Guru ® Documentation

Variability is captured in intermittent demand with the measurement of non-zero demand standard deviation $\sigma_{NZ}$. Highly variable demand is an intermittent demand with a non-zero demand standard deviation equal to or greater than four. Differently low variable demand is an intermittent demand with a non-zero demand standard deviation lower than four.

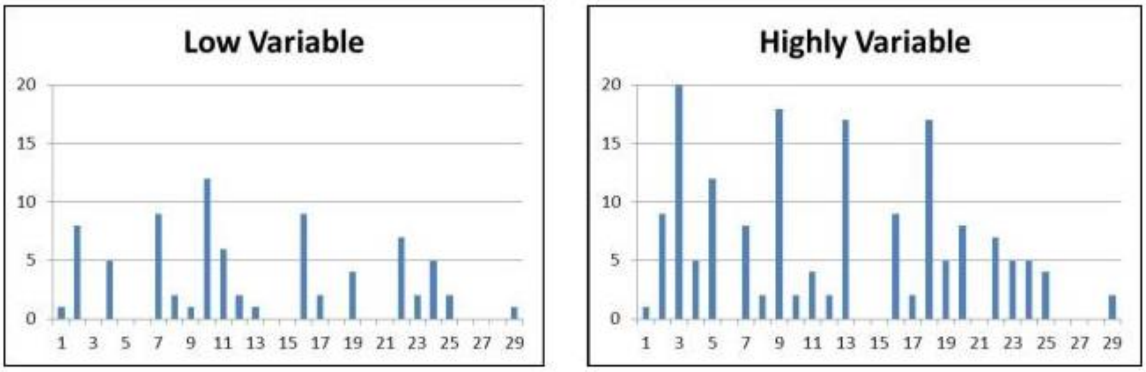



Figure 19: Graphical representation of low and highly variable demand patterns. Supply Chain Guru ® Documentation

Both highly and low variable demand are further classified in either *Slow* or *Lumpy*, using the squared coefficient of demand variation ($CV^2$) and the same cut-off value used for non-intermittent demand. Intermittent demand may be further categorized as *Clumped* if it is (almost) constant, given a non-zero demand standard deviation close to zero.

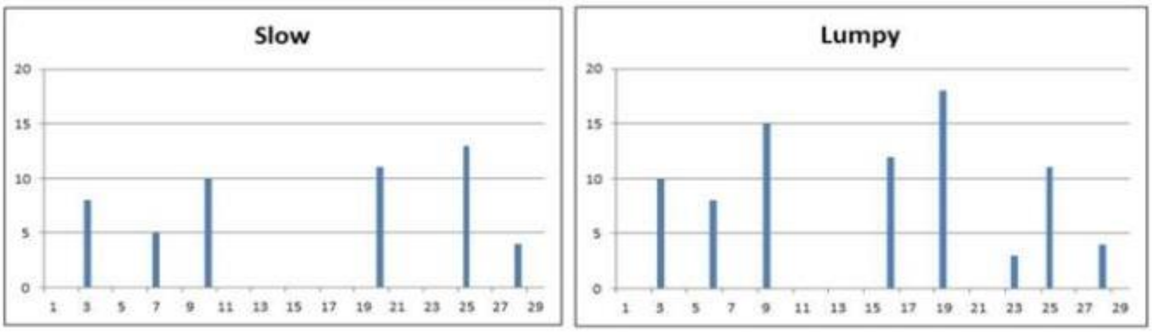



Figure 20: Graphical representation of slow and lumpy demand patterns. Supply Chain Guru ® Documentation

In summary, demand classification in *Supply Chain Guru* categorizes demand in one of the following nine demand profiles:

- *Extremely Slow*. Demand occurrence is very low (lower than three).
- *Extremely Variable*. Demand is assessed as extremely variable if the ratio between demand standard deviation and demand mean, namely coefficient

of demand variation, is greater than or equal to 5. Highly variable demand implies significant safety stock level that will be quantified in safety stock optimization output.

- *Extremely Small*. Demand with a non-zero demand mean lower than 1 is defined as not sufficiently high to allocate safety stock.
- *Non-intermittent – Smooth*. Demand is stationary and occurs at high frequency.
- *Non-intermittent – Erratic*. Demand occurs frequently in the period with significant variability.
- *Intermittent – Highly Variable – Slow*. Intermittent demand occurs with less regularity than non-intermittent demand and presents a high quantity variability expressed by non-zero demand standard deviation with a relative low variation expressed by squared coefficient of demand variation.
- *Intermittent – Highly Variable – Lumpy*. Demand occurrence is irregular, and the distribution presents high variability.
- *Intermittent – Low Variable – Slow*. Demand presents infrequent occurrences with a relatively low quantity variability in its distribution.
- *Intermittent –Low Variable – Lumpy*. Demand is irregular in terms of occurrence along the period and it results highly dispersed, although non-zero demand standard deviation does not remark a high variability.

Based on demand statistics and demand classes, a lead time demand distribution is determined.

### 4.2.3 Demand Analysis Output

At the end of demand characterization process, demand analysis provides a set of demand statistics, reported in the following output tables:

- *Aggregated Customer Demand Tables*. These tables report aggregated demand and outliers, in case that outliers have been detected during the outlier analysis.

- *Demand Profile Tables*. Demand classes and demand statistics are defined in these output tables on a period-product-site combination.

Demand profiles are presented respectively in *Customer Demand Table* for customer demand and in *Site Demand Table* for upstream-site demand, determined through demand propagation. In both Demand Profile Tables demand statistics values and demand classes are reported on scenario-site-product-period combination. This means that the demand is not left restricted to the customer-facing node of the distribution network, but for every product, the demand allocated to a given site during a specific time window is described through calculated demand statistics values and a demand class.

Specifically, the most remarkable statistics computed for customer aggregated demand are:

- **Non-zero Demand Mean ($\mu_{NZ}$).** Average product demand value during the period at a given node. The formula excludes aggregation periods in which demand does not occur (zero-demand records are not considered in the calculation).
- **Non-zero Demand Standard Deviation ($\sigma_{NZ}$).** Standard deviation of a product demand during the period at a given node. Zero-demand records are excluded.
- **Demand Mean ($\mu_D$).** Average product demand value per aggregation period allocated at a given node.
- **Demand Standard Deviation ($\sigma_D$).** Standard deviation of a product demand allocated at a given site.
- **Inter-Demand Interval Mean ($p$).** Average number of aggregation periods occurring between two consecutive aggregated demand records in the time series.
- **Non-zero Demand Squared Coefficient of Variation (${CV_{NZ}}^2$).** It is a measurement of demand variability with respect to demand mean. Its formula, recalled in the equation below, does not include aggregation periods with zero-demand.

$$CV_{NZ}{}^2 = \left(\frac{\sigma_{NZ}}{\mu_{NZ}}\right)^2$$

## 4.3 Second Stage: Multi-Echelon Inventory Optimization

Demand analysis completion sets the stage for the subsequent main step: multi-echelon inventory optimization. Given the allocation of demand throughout the whole distribution network and the corresponding demand statistics and classes, the demand-related information are available as new input data for the optimal safety stock placement.

Besides demand analysis output, replenishment lead time, replenishment frequency, production frequency, unit inventory value, target service level and stocking nodes are the necessary input information to run multi-echelon inventory optimization.

The basic structure of multi-echelon inventory optimization phase may be explained by Figure 21, showed below.

Based on demand classes and statistics, the model defines lead time demand distribution for every node: daily demand mean and standard deviation are scaled to formulate lead-time demand parameters and to assess its distribution.

Target service level and other optional model constraints, together with lead-time demand distribution are used to build a safety stock curve and after that the solver seeks safety stock coverage and corresponding service time values that result to provide the optimal safety stock level.

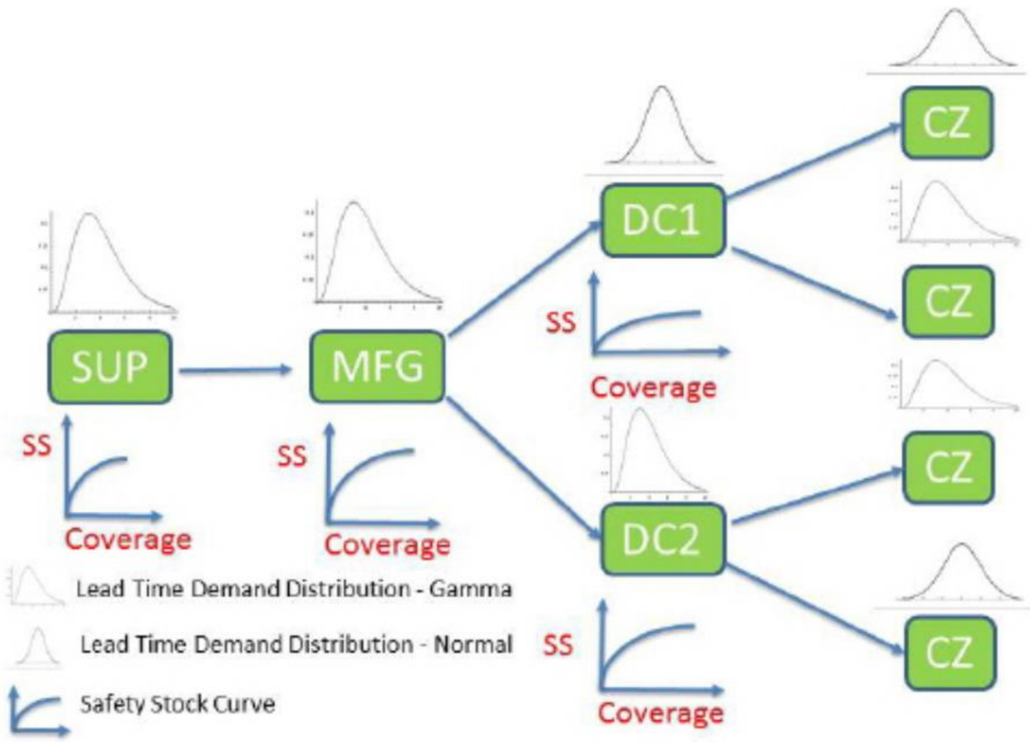



Figure 21: Graphical representation of Multi-Echelon Inventory Optimization. Supply Chain Guru ® Documentation.

In general, the number of echelons in a supply chain network raises the complexity in inventory control, since more stochastic components should be considered in decision-making processes. Safety stock allocation problem in a multi-level distribution network is addressed in *Supply Chain Guru*, using an optimization algorithm based on Guaranteed-Service Model (GSM).

In GSM approach, each echelon is assumed to guarantee a service time to its downstream echelon. The model objective is to determine the optimal service times for each network level to minimize the total inventory cost, assuring a target customer service level.

The following sections are structured so to provide theoretical overviews of multi-echelon networks and Guaranteed-service Model, as solution method for multi-echelon safety stock optimization problem. The objective is to better disclose the logic behind Supply Chain Guru optimization approach, that will be further explained.

### 4.3.1 Multi-Echelon Networks

Current real-world supply chains often comprise multiple stages at different echelon to carry out both assembly and distribution processes. These systems require an effective inventory management with the objective to minimize the total inventory costs looking at the whole network, assuring to satisfy a customer service requirement.

Multi-echelon supply chains may be defined as networks consisting of nodes, representing the stages, linked by arcs, showing the relationships and the material flow direction between two stages. An upstream node (predecessor) is directly connected to a downstream node (successor) through an arc, if the upstream stage is a direct supplier of the downstream stage.

Based on the combinations of nodes and arcs, different multi-echelon topologies may exist and can be classified as follows, in increasing order of complexity:

- *Serial systems*
- *Assembly systems*
- *Distribution systems*
- *General systems (acyclic and cyclic).*

Serial systems (Figure 22.a) are the simplest structures: each node has no more than one predecessor and successor. Assembly systems (Figure 22.b) have limitations related to the number of successors only: each node has no more than one successor. Differently, distribution systems (Figure 22.c) have limitations regarding the number of predecessors: each node cannot have more than one predecessor. General systems are the result of a synthesis between assembly and distribution systems, with no restrictions on arcs. General systems can be further divided in cyclic and in acyclic systems. General cyclic systems (Figure 22.e) allow returns of goods from a downstream stage to an upstream stage, resulting in cycles in the network structure. Contrarily, general acyclic systems (Figure 22.d) do not envisage closed loops, and thus arcs connect predecessors to successors in one direction only.

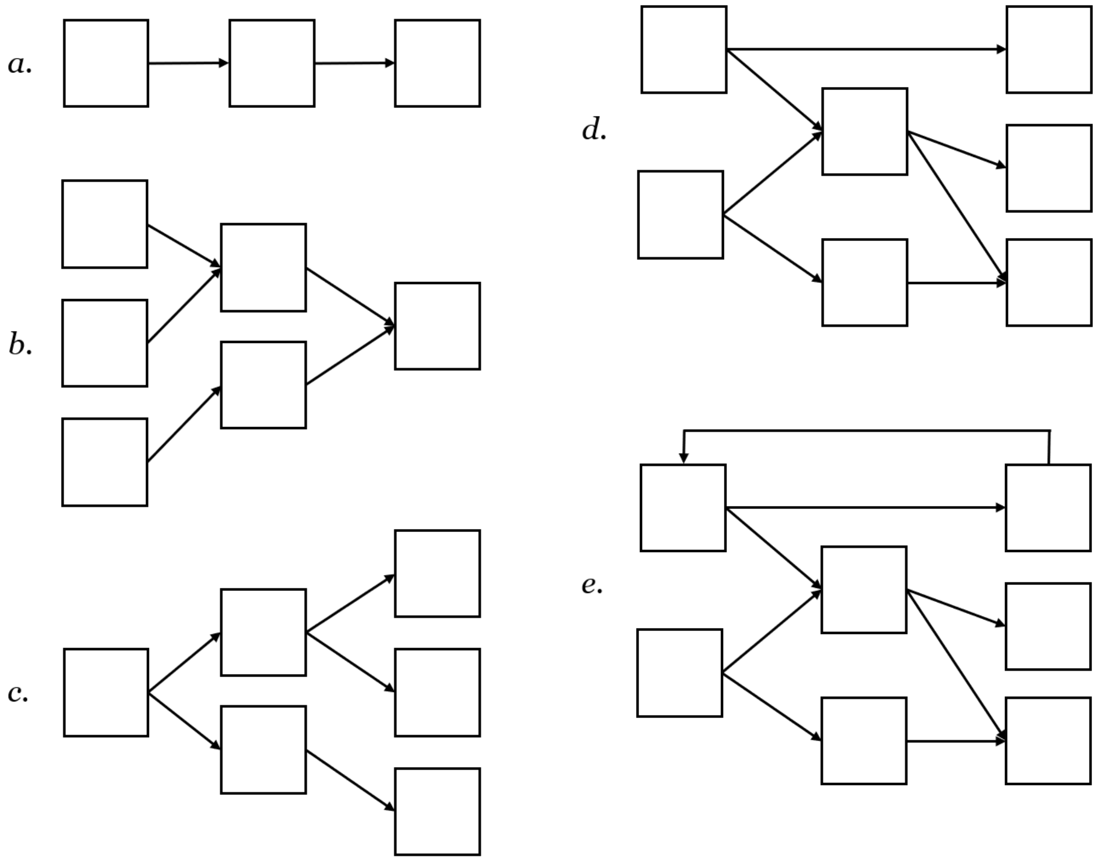



Figure 22: Multi-echelon system topologies. Representation inspired by Eruguz (2014 ).

As Willems (2008) study demonstrates, real-world supply chains are structured as general systems. Specifically, examples of general cyclic systems may be some chemical and pharma supply chains, since products are composed of products generated at downstream stages.

## 4.3.2 Multi-Echelon Safety Stock Optimization

Given the description of multi-echelon systems, multi-echelon optimization represents a complex problem, since it implies a high number of interdependent decision variables and the adoption of non-linear functions. The problem also is dependent to the number of distribution levels and to the connection types between the different levels, resulting a challenging scenario for computational models.

Specifically, multi-echelon safety stock optimization represents one of the focuses related to multi-echelon inventory optimization problem. With the target to protect against demand and lead time uncertainty, safety stock level should be optimally set at each stocking node to meet a given customer service level, minimizing the inventory cost. Single-echelon safety stock optimization is the definition of safety stock level at a given site, considering only the variables related to the specific site (such as replenishment lead time from the upstream stages, demand of downstream level, site-related inventory holding cost, customer service level etc.). This approach has been widely studied in the literature (see Silver et al., 1998; Zipkin, 2000) and largely implemented, still it neglects the interdependencies of parameters between multiple echelons of a network, if they exist.

Differently, multi-echelon safety stock optimization determines the optimal safety stock level, based on a holistic supply chain perspective, including all echelons and interdependent variables in the analysis.

Single-echelon and multiple-echelon optimization approaches are compared graphically in Figure 23.

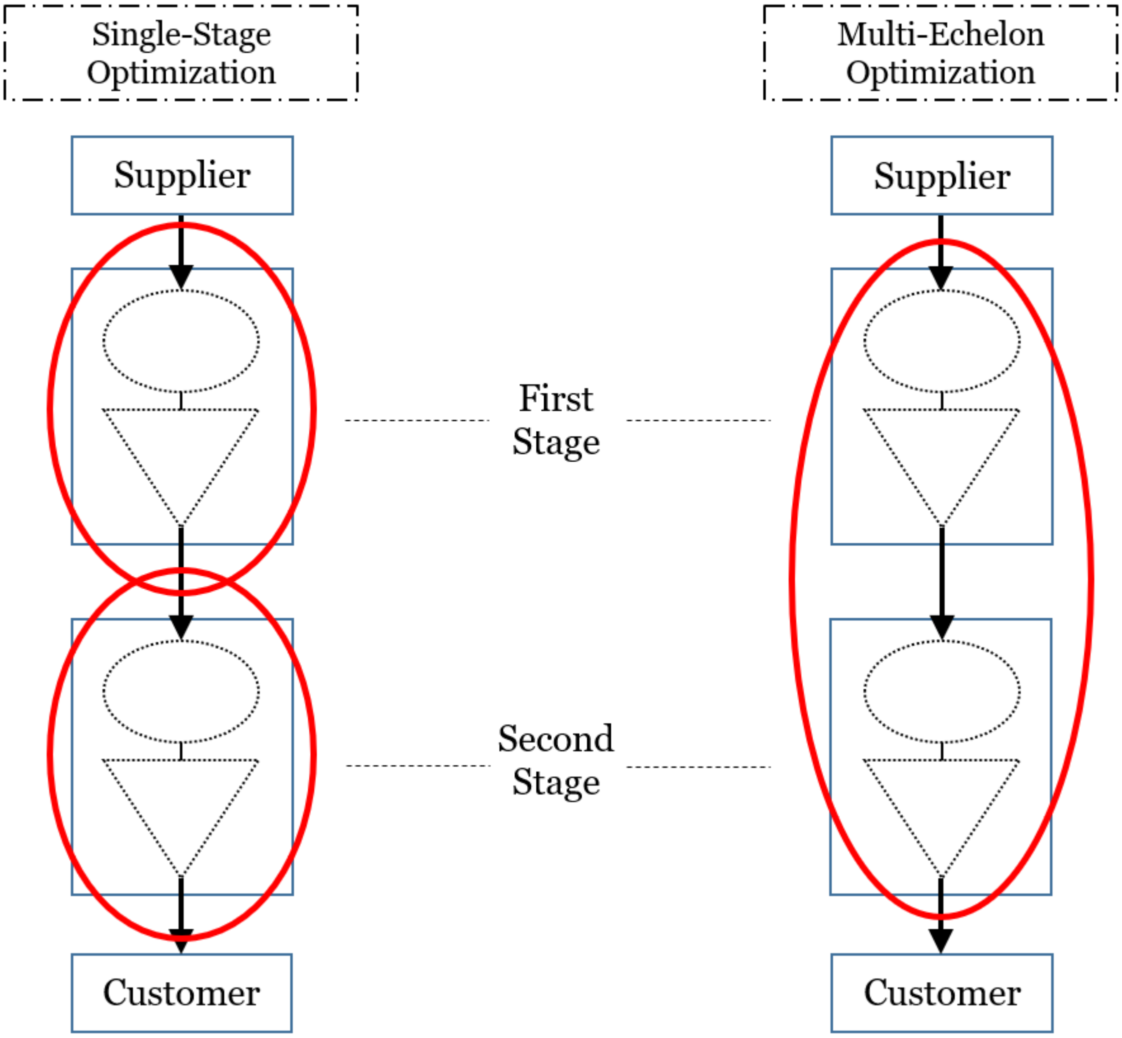



Figure 23: Single-Echelon Optimization versus Multi-Echelon Optimization. Representation inspired by Klosterhalfen (2010).

### 4.3.3 Guaranteed-Service Model

Guaranteed-service approach is a solution method widely studied in literature that addresses the problem of safety stock allocation in a multi-stage network.

GSM approach assumes that each echelon quotes a service time to its downstream echelon, after which the requested item is always available. To make this assumption hold, the demand is considered bounded in the model. Service times are the decision variables to determine, in order to meet a certain customer service requirement, minimizing the overall inventory holding cost.

Simpson (1958) represents the first attempt for formulating GSM for multi-echelon systems, and specifically considering a serial system. After some decades, the mathematical model has been interest for new studies about safety stock allocation: almost 80% of the existing works have been published between 2004 and 2014 (Eruguz, 2014). Specifically, Graves and Willems (2000) formulate GSM algorithm for multi-echelon general systems.

### *Guaranteed-Service Model Assumptions*

To describe the assumptions in Guaranteed-Service Model, Eruguz (2014) is taken as reference work.

The multi-echelon network consists of a set of nodes, denoted by **N** and a set of arcs, denoted by **A.** A scalar $\theta_{ij}$ for a couple of nodes $(i, j)$ defines the set of input units that the upstream node $i$ requires to get one output unit at the downstream node $j$, if $i$ and $j$ are connected by a direct arc.

The set of nodes **N** may be further categorized in three subsets:

- The set of supply stages $\mathbf{N_S}$ includes all stages with no predecessors.
- The set of demand stages $\mathbf{N_D}$ includes all stages with no successors.
- The set of internal stages $\mathbf{N_I}$ includes all stages with at least one predecessor and one successor.

Assume a node $j \notin \mathbf{N_D}$, resulting either a supply stage or an internal stage of the system. For each $j$, $\mathbf{N_D}(j)$ denotes the set of demand stages connected to node $j$ through a direct arc.

The Guaranteed-Service model presented below refers to Graves and Willems (2000) version. The assumptions considered valid in this model are the followings:

1. Time is phased in periods of equal length. Planning horizon is assumed infinite in the model.

2. Each stage can issue orders when a time period starts (that means that all stages have a review period of one-period length). Inventory control at each stage is based on periodic-review, order-up-to policy.
3. Lead time is deterministic, constant in time and an integer value (multiple of the unit period). The lead time at the customer-serving stage includes one-period long review period.
4. No storage capacity constraint is assumed at each stage.
5. External suppliers have unconstrained capacity.
6. Inventory holding cost is assumed with a linear structure.
7. Customer demand is allocated to the most downstream node (demand stage). Hence, the external demand $d_j(t)$ occurring at demand stage $j \in \mathbf{N_D}$ is identically and independently distributed ($i.\ i.\ d.$) on [0, ∞), with a mean $\mu_j$ and a standard deviation $\sigma_j$ in each period.

   Non-demand stages do not have external demand, but they respond to internal demand coming from their immediate successors. Thus, demand $d_i(t)$ at non-demand stage $i \in \mathbf{N_S} \cup \mathbf{N_I}$ in period $t$ is equal to the sum of orders issued by its immediate downstream stage. Demand $d_i(t)$ at non-demand stages may be expressed by the formula:

$$d_i(t) = \sum_{j:(i,j)\in A} \theta_{ij}\, d_j(t)$$

8. The model assumes a bounded demand with an increasing and concave function $D_j(\tau_j)$ for each stage $j \in \mathbf{N}$ and for each period $\tau_j = 1,2,\dots,M_j$, given that $M_j$ stands for the maximum time occurring between the order and the reception of the considered item at stage $j$ (called maximum replenishment time). Maximum replenishment time $M_j$ is computed by the formula:

$$M_j = L_j + max\{M_i | i :\ (i,j) \in \mathbf{A}\}$$

Where $L_j$ represents the average lead time at each stage $j$, being the average process time at stage $j$, given that all required input items are available to start the process at that stage.

In this framework, for any period $t \geq \tau_j$ and for every node $j \in \mathbf{N}$ the following is considered true:

$$D_j(\tau_j) \geq d_j(t - \tau_j, t)$$

Noting that

$$d_j(t - \tau_j, t) = 0 \; for \; t - \tau_j \geq t$$

$$d_j(t - \tau_j, t) = \sum_{T=t-\tau_j+1}^{t} d_j(T) \; for \; t - \tau_j \leq t$$

In summary, demand bounds represent the maximum demand that is covered by safety stock. When demand exceeds $D_j(\tau_j)$ over the net replenishment time $\tau_j$, safety stock is not enough to buffer against the demand surplus.

The original GSM does not include explicit measures for meeting demand excesses, not covered by safety stock. It does not calculate monetary costs of such measures, but it relies on the concept of operating flexibility. Companies should envisage this potential situation and provide with specific corrective actions to minimize losses.

Nonetheless recent studies aimed at finding solutions for the gap of GSM with uncovered demand surplus. Rambau and Schade (2010), for instance, introduced a stochastic programming variant of GSM, proposing entire recourses for delays and uncovered demand.

9. Each node $j \in \mathbf{N}$ ensures an outbound service time $s_j^{out}$ to its immediate successor node, such that the demand $d_j(t)$ occurring at node $j$ in period $t$ is entirely met at period $t + s_j^{out}$. In parallel an inbound service time $s_j^{in}$ denotes the time that each node $j$ has to wait to obtain all requested input items from predecessors $i$ such that $(i, j) \in \mathbf{A}$ to start the process at node $j$. The condition that the process cannot begin at any stage if all necessary input items are available at that stage, implies that

$$s_j^{in} \geq s_j^{out} \text{for all arcs } (i, j) \in \mathbf{A}.$$

Outbound and inbound service times result the decision variables in GSM: they are determined so that the overall inventory holding cost is minimized and that a target customer service requirement is met.
Service times assume integer values, and they can be multiples of the unit time bucket.

The underlying assumptions of GSM approach are outlined in Table 7.

| **Graves and Willems (2000) Guaranteed Service Model Assumptions** | |
|---|---|
| External Demand | Stationary and bounded |
| Lead Times | Known and constant |
| Capacity Constraint | Not considered |
| Service Time | Constant and equal for all successors of one stage |
| Inventory Management Policy | Periodic review and order-up-to inventory policy. Review period is set equal for all stages |
| Countermeasures for uncovered demand and delays | Not explicitly considered |

Table 7: Summary of original GSM assumptions. Representation inspired by Eruguz (2014)

## *Guaranteed-Service Model Inventory Dynamics*

Based on the model assumptions, the underlying inventory dynamics of GSM may be disclosed.

The demand $d_j(t)$ occurring at stage $j$ is observed at the beginning of period $t$, and this triggers an order issued by stage $j$ corresponding to the demand $d_j(t)$.

The ordered quantity is available at stage $j$ at period $t + s_j^{in} + L_j$.

Equally stage $j$ promises to fulfill the demand at period $t + s_j^{out}$.

If the replenishment order corresponding to the demand $d_j(t)$ is carried out after the period in which $d_j(t)$ is served, stage $j$ requires enough available inventory to cover this demand. In other words, if $s_j^{in} + L_j > s_j^{out}$ the inventory level at stage $j$ should be sufficient to satisfy the demand over the period $\tau_j = s_j^{in} + L_j - s_j^{out}$, which goes by the name of "net replenishment time" at stage $j$.

We assume that for any period $t \leq 0$ demand $d_j(t)$ is equal to 0 and the initial inventory level $I_j(0)$ at stage $j$ is equal to $S_j \geq 0$.

Graves and Willems (2000) proposed a balance equation for the net inventory level $I_j(t)$ at stage $j$ at the end of period $t$, that is:

$$I_j(t) = S_j - d_j(t - s_j^{in} - L_j, t - s_j^{out})$$

The interval $t - s_j^{in} - L_j$ stands for the last replenishment collected at stage $j$ by time $t$, while $t - s_j^{out}$ represents the last demand fulfilled by stage $j$ by time $t$. This is equal to say that at any time stage $j$ should hold inventory to cover the time $s_j^{in} + L_j - s_j^{out}$, which is equal to its net replenishment time.

The order-up-to level $S_j$ should be equal to the upper demand bound $D_j(\tau_j)$. Given this condition, the expected inventory level $E[I_j(t)]$ can be determined as follows:

$$E[I_j(t)] = D_j(\tau_j) - \tau_j \mu_j$$

Where $\mu_j$ denotes the demand mean at stage $j$ and $\tau_j$ is the net replenishment time of stage $j$. The expected inventory level $E[I_j(t)]$ corresponds to the safety stock level kept at stage $j$.

## ***Guaranteed-Service Model Mathematical Formulation***

Given the assumption (6) of linear inventory holding cost structure, the GSM problem to determine the optimal inbound and outbound service times that minimize the total inventory cost of the network can be formulated with the following objective function:

$$P0\colon min \sum_{j \in N} h_j \left\{ D_j(\tau_j) - \tau_j \mu_j \right\} \qquad (1)$$

Such that

$$\tau_j = s_j^{in} + L_j - s_j^{out} \qquad \forall j \in \mathbf{N} \qquad (a)$$

$$s_i^{out} \leq s_j^{in} \qquad \forall (i,j) \in \mathbf{A} \qquad (b)$$

$$s_j^{out} \leq s_j^{client} \qquad \forall j \in \mathbf{N_D} \qquad (c)$$

$$\tau_j, s_j^{out}, s_j^{in} \geq 0 \; and \; integer \qquad \forall j \in \mathbf{N} \qquad (d)$$

In the objective function $h_j$ denotes the unit inventory holding cost at stage $j$, while (a), (b), (c), (d) define the constraints to the objective function. Once the problem $P0$ is solved, the optimal order-up-to level $S_j^*$ is determined with the equation $S_j^* = D_j(\tau_j^*)$, in which $\tau_j^*$ corresponds to the optimal net replenishment time at stage $j$.

The solution method adopted in Graves and Willems (2000) is the dynamic programming, which is largely used for optimization problems.

The GSM version disclosed so far refers to Graves and Willems (2000) study, which considers Simpson (1958)'s work and extends it for general multi-echelon systems. Table 7 summarizes the main assumptions of Graves and Willems (2000). Nonetheless, the underlying assumptions have been interests of several researchers, who published their works focused on the relaxation of GSM assumptions. For instance, see Graves and Willems (2008) and Neale and Willems (2009) for the extension of GSM with non-stationary demand assumption. Relaxation on lead time assumptions has been examined in Inderfurth (1993), Minner (2000) and Humair et al. (2013). In this work, the original GSM has been presented with the purpose to disclose the basic logic behind the model for the understanding of the industrial application through *Supply Chain Guru*.

### 4.3.4 Multi-Echelon Safety Stock Optimization in Supply Chain Guru

Supply Chain Guru embeds Safety Stock Optimization model, appropriate for a multi-echelon network. This model, as already mentioned, is founded on GSM approach. Specifically, based on the objective function (1) reported in the previous subsection, Supply Chain Guru obtains the optimal safety stock level at each stage of the network.

Indeed, the key parameters for the GSM optimization objective function may be retraced in SCG Safety Stock Optimization.

First, unit inventory holding cost $h_j$ is expressed in the software with two possible fields: Product Value and Product Inventory Value. They are both input fields, but the main difference between them is that Product Inventory Value denotes the unit item value at a specific stage (namely “site” in the software), while Product Value corresponds to unit item value regardless the stage where it is stored. Product Inventory Value is preferred to Product Value when there exists a cost difference in terms of storage location. If Product Inventory Value field is populated, it overrides Product Value and it is considered the unit inventory cost in the optimization objective function.

Second, net replenishment time $\tau_j$ corresponds to time in which demand occurs and it should be covered by safety stock at stage $j$. This concept appears in Supply Chain Guru too and it goes by the name of "Coverage". Recalling the net replenishment time formula, coverage can be expressed as:

$$Coverage = \tau_j = s_j^{in} + L_j - s_j^{out}$$

Inbound $s_j^{in}$ and outbound $s_j^{out}$ service times are the decision variables of the objective function and they assume integer values. Note that for any pair of stages $(i, j)$ connected by a direct arc, which specifies that node $i$ is the predecessor of stage $j$, the inbound service time $s_j^{in}$ at stage $j$ is equal to the outbound service time $s_i^{out}$ quoted by stage $i$. In other words, $s_j^{in} = s_i^{out}$. Moreover, the outbound service time $s_i^{out}$ that any stage $i$ promises, is common for any immediate downstream stage $j$ of stage $i$.

The outbound service time $s_j^{out} = 0$ for any $j \in \mathbf{N_D}$. The assumption states that the most downstream stages, which serve directly external customers, promise a null service time to its clients. Note that service times do not include transit time.

About lead time parameter $L_j$, the concept of immediate lead time $ILT$ can be recalled from Capitolo 4. Indeed, immediate lead time consists of the different lead time components, depending on the type of node.

Specifically, if stage $j$ is a production stage for the item $k$, the immediate lead time $ILT_{kj}$ is computed as follows:

$$ILT_{kj} = Fixed\ Production\ Time_{kj} + Review\ Period_{kj}$$

Differently, if stage $j$ is not a production stage for the item $k$, but it is replenished by an upstream stage $i$, the immediate lead time $ILT_{kj}$ is formulated as:

$$ILT_{kj} = Sourcing\ LT_{kij} + Transportation\ LT_{kij} + Review\ Period_{kj}$$

If item $k$ directly flows to the stage $j$ from more than one sourcing point, a multiple sourcing policy applies and a fraction of sourcing quantity is associated to each sourcing node.

Thus, coverage (or net replenishment time) can be expressed with the following formula, in which the lead time component is replaced by the corresponding immediate lead time:

$$Coverage_{kij} = s_j^{in} + ILT_{kij} - s_j^{out}$$

Supply Chain Guru provides with two different solution techniques for Multi-Echelon Inventory Optimization problem:

- Dynamic programming. This method is selected for limited-size models and tree structure networks (general acyclic multi-echelon systems).
- Linear programming. This method is selected for complex networks, since it can handle general cyclic multi-echelon systems.

The selection of one solution technique depends on the complexity and on the size of the problem.

### *Multi-Echelon Inventory Optimization Output*

In the previous sections, the second stage of Multi-Echelon Safety Stock Optimization in Supply Chain Guru has been disclosed, through an introductory overview on the theoretical bases about both multi-echelon systems and Guaranteed-service model, followed by an explanation of the software optimization model components and logic.

In this section, the output of Multi-echelon Inventory Optimization model is presented.

The key inventory-related output elements are:

- **Safety stock**, expressed in the quantity unit of measure defined by the user, is determined through the optimization objective function (1).

- **Safety stock** (**Days of Stock**); it is the number of days of supply as safety stock to protect against either demand or lead time variations. It is derived from:

$$SS\ (DOS) = \frac{Safety\ Stock\ (Quantity)}{Daily\ Demand\ Mean\ \left(\frac{Quantity}{Day}\right)}$$

  Where $Daily\ Demand\ Mean\ (DDM) = \frac{(aggregated)\ Demand\ Mean}{Number\ of\ days\ in\ 1\ aggregation\ period}$

- **Coverage** (in days); it is obtained through the optimization that determines the optimal service times.
- **Cycle Stock** (in quantity); Supply Chain Guru calculates the cycle stock level of a given item at a given site with the following formula:

$$CS = \frac{max(MOQ, RF \times DDM)}{2}$$

  Where $MOQ$ is the Minimum Order Quantity and $RF$ is the replenishment frequency.

The reported output parameters are only few of the set of information provided by Supply Chain Guru, which is not wholly explained in this section, because not strictly within the project scope.

Further model optimization output results in the recommendation of specific inventory control policies, based on the demand class to which a product demand belongs.

The process steps Safety Stock Optimization in Supply Chain Guru follows are (1) through demand analysis demand statistics and demand classes are defined for any product demand (2) Lead time demand is therefore examined and a lead time demand distribution is estimated (3) Inventory control policies are specifically recommended according to the demand class (4) Inventory control policies parameters, such as reorder point and reorder quantity, are determined as well.

Table 8 summarizes the combinations between demand class, defined in demand analysis, lead time distribution type and the recommended policies for inventory management.

| Demand Class | Lead Time Demand Distribution | Recommended Inventory Management Policy | Recommended Inventory Review System |
|---|---|---|---|
| Extremely Slow | | Make-to-order | |
| Smooth | Normal | Reorder Point, Reorder Quantity (R,Q) | Continuous |
| Erratic | Gamma | Reorder Point, Order up-to (s,S) | Continuous |
| Low Variable – Slow (with unitary batch size) | Gamma | Base stock | Continuous |
| Low Variable – Slow (with batch size >1) | Gamma | Reorder Point, Reorder Quantity (R,Q) | Continuous |
| Highly Variable – Slow | Gamma | Reorder Point, Order up-to (s,S) | Periodic |
| Lumpy (with unit batch size) | Negative Binomial/Gamma | Periodic review order-up-to | Periodic |
| Lumpy (batch size>1) | Negative Binomial/Gamma | Reorder Point, Reorder Quantity (R,Q) | Continuous |
| Extremely Small | | Not necessary | |
| Extremely Variable | | | |

Table 8: Recommended Inventory Control Policies for Demand Classes. Supply Chain Guru ® Material

Specifically, Reorder Point Policy is an inventory control policy that implies the placement of a replenishment order when the inventory position goes below a specific inventory threshold, namely reorder point (R). A necessary condition for the implementation of reorder point policy is a continuous review period, which guarantees that when the inventory level gets below the reorder point, it is immediately detected. The reorder quantity (Q) is defined as well as the reorder point (R). Reorder Point policy is appropriate for smooth demand class and for fast-moving items, for which economies of scale in the supply network are high. Supply Chain Guru computes reorder point (R) and reorder quantity (Q) of a given item $k$ at any stage $j$ as follows:

$$R_{k,j} = Lead\ Time\ Demand\ Mean_{k,j} + SS_{k,j}$$

$$Q_{k,j} = \text{Minimum Replenishment Quantity} = \max(MOQ, RF_{ij} \times DDM_{k,j})$$

Where $RF_{ij}$ corresponds to the replenishment frequency from the upstream stage $i$ to its immediate downstream stage $j$, while $DDM_{k,j}$ corresponds to the daily demand mean of item $k$ at stage $j$.

Another appropriate model with continuous inventory review systems is Reorder Point, order-up-to Policy. This policy implies a reorder point, namely $s$, as in the previously mentioned policy. When the inventory position ($IP$) undergoes the set reorder point $s$, a replenishment of quantity $S - IP$ is requested. The system does not work with a constant reorder quantity, but with a fixed order-up-to inventory level ($S$). This inventory management policy is suitable for handling highly-variable demand items, since demand variations are dealt with order-up-to level ($S$) and the reorder timing decision is dealt with reorder point ($s$). Supply Chain Guru computes the policy parameters for item $k$, stored at stage $j$ as follows:

$$s_{k,j} = Lead\ Time\ Demand\ Mean_{k,j} + SS_{k,j}$$

$$S_{k,j} = s_{k,j} + \text{Minimum Replenishment Quantity} = s_{k,j} + \max(MOQ, RF_{ij} \times DDM_{k,j})$$

With a periodic inventory review system, Min Max system (or order-up-to level policy) is suitable for managing items with an intermittent-demand that is highly variable along time (classified as "Lumpy" items in demand analysis). The inventory position ($IP$) is controlled periodically (every $T$ periods), and when $IP$ is detected to be below a minimum threshold (s), a replenishment order of variable quantity is placed. The replenishment quantity is set so that an order-up-to level is reached. This policy permits the consolidation of replenishment shipments and may be not appropriate with fast-moving items, since periodic review does not guarantee a short reaction time.

Base-stock policy is a different inventory control policy that assumes a replenishment order placement any time that a demand occurs, without considering batching. This is consistent with slow-moving and highly-valuable products and with negligible scale economies. A recommended condition for the implementation of such policy is the presence of a continuous inventory review system, so that the system reactivity is facilitated.

Safety Stock Optimization collects the overall output data in two main tables:

- Inventory Policy Summary Table;
- Inventory Policy Details Table.

While Inventory Policy Summary Table gathers all general output information based on a site-product combination, Inventory Policy Details table shows the details about service times and coverage for each product-site combination.

# CHAPTER 5
# IMPLEMENTATION

## 5.1 Multi-Echelon Inventory Optimization Pilot Model

The investigation of optimal level for safety stock in Barilla distribution network has been performed through Safety Stock Optimization model of *Supply Chain Guru* software. In order to test its validity as a tool and its responsiveness to the company's needs, a model application was required.

The Inventory Optimization model in Supply Chain Guru has been built on a single time period and based on actual input data about Barilla supply chain, referring to a time period of one year, starting from January 2017 to December 2017.

Specifically, a pilot regional warehouse has been selected from Barilla distribution network so that it could be representative of all others. Indeed, the shipped quantity from this hub is significant (more than 15000 tons per year) and the number and categories of handled items is in line with the other six regional warehouses in Italy.

The model has been populated with as-is supply chain data, with the purpose to benchmark model output inventory values with the values assessed through the current inventory control system of the company, and for a final validation of the model itself. The details and reasons of the considered system boundaries will be disclosed in the following sections.

### 5.1.1 Demand

The demand inserted in the model considers the demand allocated and served by one hub, which has been taken as reference for the pilot model. Demand series has been provided on daily basis and considering actual customer orders received from January 2017 to December 2017. The selected quantity unit of measure was boxes, since it is the unit of measure used in the operating functions for calculating product stocks.

### 5.1.2 Products

By being replenished by most of company's plants and by being designed to cover the whole customers' demand in specific geographical areas, Barilla regional warehouses usually handle the whole product range, encompassing all Group brands marketed in Italy (*Barilla, Mulino Bianco, Pavesi, Wasa, Barilla Food Service*). The average number of shipped trade units from hubs is 800.

However, some specific item categories have been removed from the considered demand.
Items that have been launched by Barilla during the calendar year have not been included, since their demand could not be distributed along the whole year, causing misleading results in demand analysis. For the same reason, those products, whose production has been stopped during the year have been excluded from the model demand.

Moreover, among all trade units there are specific items labelled as "*item in allocation*", which are sold in specific periods of the year with no significance in their demand series, since they are associated to exclusive events or trade promotional campaigns. For example, they can be products given for free to trade customers, together with a quantity promotion on sales.

Given their demand singularity and their irregularity in the inventory level, they have been excluded from the demand analysis.

Among all items handled in hubs, a broad category is represented by *repacked items*, specific products that are sold as repacked to trade customers for commercial or marketing reasons. Repacked items ordered volumes have been included from the model demand, since they often significantly impact on the total outbound volumes of the corresponding base item. For instance, 1 repacked item A could be composed of three boxes of product A. Since demand for repacked items is increasing more and more in the food retail distribution, it is significant not to exclude volumes of these products from the analysis.

Generally, the demand database has been determined in such a way that considered items could have substantial sales volumes, and that results on demand patterns could be significant. Indeed, since demand for few items occurred less than three times in a year with not significant quantity, these items were removed from the model demand.

### 5.1.3 Network

From a geographical point of view Italian distribution network represents the study focus, and more specifically SSO is restrained to Barilla regional warehouses, or *hubs*, which amount to seven. The network injected in the model has been built in such a way that could support and serve the demand of the area covered by the pilot hub.

Plant warehouses are included in the model and the software computes inventory levels and recommended inventory policies also for their inventories, given the demand restricted to the hub only.

Additional production sites in the model are represented by foreign company plants as well as co-producers, or *co-packers*, being the points of origin for some specific products requested in Italian market. Most co-packers are located in Italy, while foreign Barilla plants are located in Europe and they are connected to Italian nodes through road transportation.

Additionally, auxiliary warehouses represent accumulation points in the real network, which support central warehouses, by providing extra storage area. They are sourced by both internal plants and co-packers and they often replenish the same plant warehouses. Two main reasons drove the decision to exclude auxiliary warehouses from the optimization model.

First, their presence generates closed loops in terms of flows that are not supported by the Safety Stock Optimization tool.

Second, every year Barilla drafts and signs a contract with 3PL that determines storage area to be rent and the annual storage tariffs for each auxiliary warehouse. The number and the choice of auxiliary warehouses differ from year to year, according to annual storage needs, and so, including these nodes within the model network, the strategic perspective of the optimization model would be undermined.

Safety Stock Optimization holds the model assumption that the stocking nodes have unconstrained storage and throughput capacity.

Through geocoding capabilities, *Supply Chain Guru* provides with a map of the sites entered in the model, and Figure 24, extracted from the software visual outputs, shows the geographical distribution of the model nodes (green triangles).

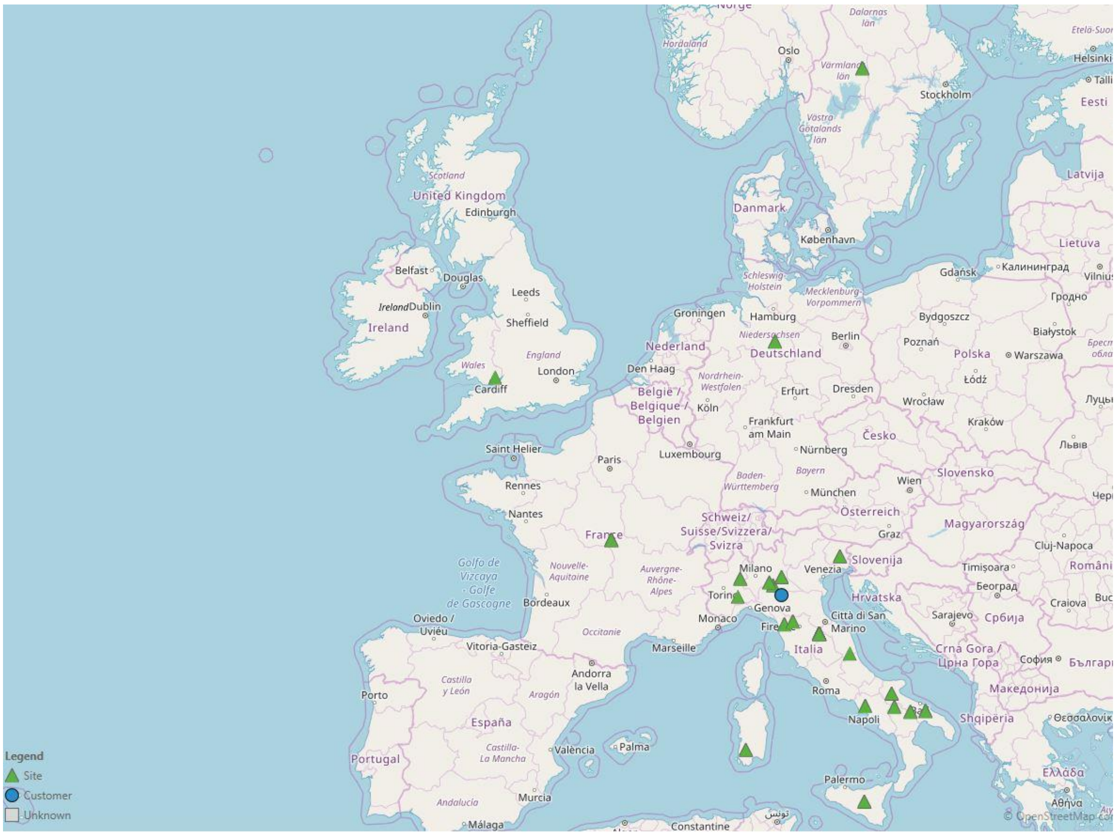



Figure 24: Geocoding of Model Sites. Supply Chain Guru®

## 5.1.4 Lead Times

Lead times have been calculated on lane basis. Lead time mean and standard deviation have been computed based on data regarding all actual shipments occurred in the calendar year 2017.

Sourcing lanes have been traced based upon historical data, to build actual sourcing flows of each demanded item. Thus, given the historical (real) sourcing network, all items flowing from one specific upstream node to a downstream one present the same lead time mean, lead time standard deviation. Replenishment frequency has been calculated as the ratio between the number of historical shipments of a given item occurred for a specific lane and the total number of working days for shipments in 2017. The replenishment frequency has been determined on item and lane basis, resulting an accurate value for expressing how often an item is on average shipped from one site to a destination site in Barilla network.

The computation of lead times has included all journeys occurred from one node to another. No differentiation has been applied to "urgent" shipments, which are the ones that anticipate delivery by one day upon extraordinary customer requests. This decision was mainly driven by their negligible incidence on total number of journeys performed on a specific lane (around 1 percent of all trips).

Recalling that the optimization model splits lead time in sub components, such as *Sourcing Lead Time*, *Transportation Lead Time*, *Review Period*, *Production Lead Time*, the methodology adopted to determine these lead times is presented below. *Immediate Lead Time* ($ILT_{j,i}$) of a non-production site $i$ replenishment from an upstream site $j$ corresponds to the sum of Sourcing LT, Transportation LT and Review period, as reported by the following formula:

$$ILT_{j,i} = Sourcing\ LT_{j,i} + Transportation\ LT_{j,i} + Review\ Period_i$$

Figure 25 illustrates how immediate lead time for a given lane is built up, assuming it is common for all items moved along the lane from $i$ to site $j$ and assuming that site $j$ is not a production stage. Note that $SLT_{ji}$ corresponds to sourcing lead time, $TLT_{ji}$ corresponds to transportation lead time and $RP_i$ corresponds to inventory review period.

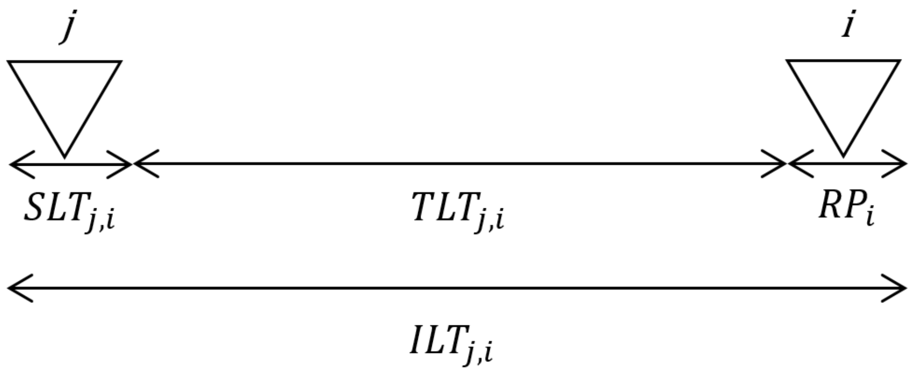



Figure 25: Immediate Lead Time composition

The annual mean and standard deviation values of *Sourcing Lead Time* and *Transportation Lead Time* have been formulated for every inter-site lane and for the route from the hub to final customer. *Sourcing Lead Time* has been assumed as the amount of time elapsed between actual order creation date and actual order loading date. *Transportation LT* was assumed as the amount of time elapsed between an actual order loading date and the actual arrival date. Inventory Review Period was entered as a common interval value for every stocking site in the network, since the inventory control is centralized.

Recalling that *Immediate Lead Time* ($ILT_{j,i}$) of a production site $i$ replenishment from an upstream site $j$ is the sum of *Fixed Production Time* and *Review period,* as showed in the formula:

$$ILT_{j,i} = Fixed\ Production\ Time_{j,i} + Review\ Period_i$$

Fixed Production Time has been set equal to all production sites, since it neglects the lot size and can be approximated to a value common for all plants.

### 5.1.5 Inventory Holding Costs

The optimization algorithm requires a unitary product cost as input datum. LLamasoft considers *Product Value* or alternatively, *Product Inventory Value*, if entered in Inventories Policies Input Table, as unit cost variable for the objective function. The main difference is that *Product Inventory Value* expresses a value for the item considering the stocking site where it is located, since *Inventory Policies Table* reports input information regarding a specific demanded item stocked in a specific site of the network.

Differently *Product Value*, which is entered in *Product Table*, is unique for each item, regardless its stocking position along the distribution network. Since inventory-related costs vary according to storage locations along Barilla distribution network and since these costs impact on inventory value (and therefore also on safety stock value), *Product Inventory Value* becomes a significant field to be specified in the model.

With the purpose to express how product inventory-related cost changes from node to node in the real network, *Product Inventory Value* has been built by summing unit storage cost ($SC$), unit inbound and unit outbound handling costs ($IHC$ and $OHC$), as shown in the following formula:

$$PIV_{x,y} = \sum SC_{x,y}, IHC_{x,y}, OHC_{x,y} \text{ for every item } x \text{ located in node } y.$$

In the model optimization this value overrides *Product Value*, which was conceived as generic Cost of Good Produced (COGP) and so lacking of valuable information for an inventory allocation problem.

### 5.1.6 Service Level

Among the available service definition options, Item Fill Rate was selected. The choice was mainly driven by the actual adoption of IFR as service performance indicator by Barilla, making it easy to determine and to express as a target value for the purpose of the model.

Quantity fill rate is calculated as the ratio between shipped quantity and ordered quantity of a given item during a given time frame. Barilla is not responsible for delivering and transporting goods to final customer, since these activities are carried out by a logistics provider. For this reason, the considered performance indicator is expressed as the ratio between shipped quantity and ordered quantity, as shown below:

$$IFR_i = \frac{Tot.Shipped\ Quantity_i}{Tot\ Ordered\ Quantity_i}$$

### 5.1.7 Model Constraints

Inventory Optimization in Supply Chain Guru provides with multiple model constraints that may be defined to enrich the model specificity, according to the user's needs.

The objective function is subject to the customer service requirement, pointed out at site-product level. Besides, there was the necessity to enter a constraint concerning the maximum stock coverage. Indeed, by handling perishable goods, Barilla inventory planning has to consider the maximum number of days that each item can be held as inventory to be eligible for the sale.

The maximum stock coverage value is determined on item basis by Barilla inventory planning unit, considering the item deadline for disposal that depends both on the product ingredients (raw materials) and on the required time for distribution. This constraint value becomes extremely relevant in the inventory planning of fresh-bakery products that have demanding times, to not end up with inventory adjustments.

A new constraint as “maximum stock coverage” has been introduced in the model to ensure that the optimal safety stock level did not exceed the maximum number of days of stock, set for distribution-related issues.

The maximum stock coverage constraint is defined in the input “Inventory Policies Table” in the field “Max Safety Stock DOS”. This constraint can be specified on each item stored at a given stocking site in the model.

The input parameters in the implemented Safety Stock Optimization model are summarized in Table 9.

| Input Element | Input Model Datum |
|---|---|
| **Customer Demand** | |
| Demand Type | Historical Demand Series |
| Time Period | Calendar Year 2017 |
| Market Region | Italy Market |
| Demand Boundaries | Demand allocated to the pilot hub |
| **Products** | |
| Business Category | Food |
| Brand | All Barilla brands marketed in Italy |
| Number of SKUs | Around 450 SKUs |
| **Network** | |
| Number of Network Nodes | Around 30 |
| Type of Sites | Barilla and suppliers' plants, warehouses |
| Replenishment Frequency | Defined on item basis |
| Sourcing Policy | Single/Multiple sourcing policies |
| Site Capacity Constraint | None |
| Demand-serving node | One single regional warehouse |
| **Inventories** | |
| Unit Inventory Holding Cost | Product Inventory Value |
| Inventory Review Period | Common to all nodes |
| Max Safety Stock DOS Constraint | Set on item basis |

| Customer Service Level | |
|---|---|
| Service Requirement | Item Fill Rate |

Table 9: SSO Model implementation: input information

## 5.2 Results

The application of the multi-echelon safety stock optimization has implied many activities for input data entry, disclosed in the previous section.

So far, the sourcing network has been fixed in the optimization tool, with the data concerning actual production, replenishments and lead times referred to the considered period. Demand has been entered as historical series on daily basis, considering also the outbound volumes in form of repacked items.

### 5.2.1 Demand Analysis

To facilitate the understanding of demand analysis results, a classification was applied to the demanded items based on the total shipped quantity from the considered hub. Demanded items entered in the model have been clustered in the following categories:

- *AA*, including those items generating 50% of total shipped quantity.
- *A*, including those items that contribute to generate 80% of total shipped quantity.
- *B*, including those items that contribute to generate 95% of total shipped quantity.
- *C*, including those items that contribute to the remaining 5% of total shipped quantity.

The classification was based on the outbound volumes included in the demand model, measured in boxes, being the unit of measure utilized for outbound shipments from Barilla depots.

The classification was done for analysis-related purposes and not as a specific activity required by the optimization model.

Demand analysis has been run on a weekly basis, that implies that the aggregation period taken for formulating demand statistics and assessing demand classes is one week.

Specifically, a five-working-day week has been considered as time bucket, given that customer orders occur from Monday to Friday only. The decision to assume a weekly aggregation period for running the demand analysis in Supply Chain Guru was driven mainly by two reasons.

First, the ability to obtain an acute study able to capture demand patterns in greater detail than a monthly-based analysis, which would pool more demand records and would not identify significant demand variations for analysis purposes. Indeed, since historical demand input data have been entered as daily series in the model, a weekly bucket phasing of demand can still ensure significant quantities to be representative for a demand pattern study, highlighting potential features such as intermittency and variation.

Second, since the safety stock optimization model is expected to be working with forecasted ordered quantity, the model simulation would have more significance in adopting the same time bucket as the forecast demand, which is a weekly input information. Thus, a weekly-based demand analysis could reveal consistent outcomes with the expected utilization of the optimization model.

Demand analysis, run on a five-day weekly bucket, revealed that in general, most items (more than 90%) included in the analysis, show a non-intermittent demand pattern, meaning that their demand occurs relatively frequently in all periods.

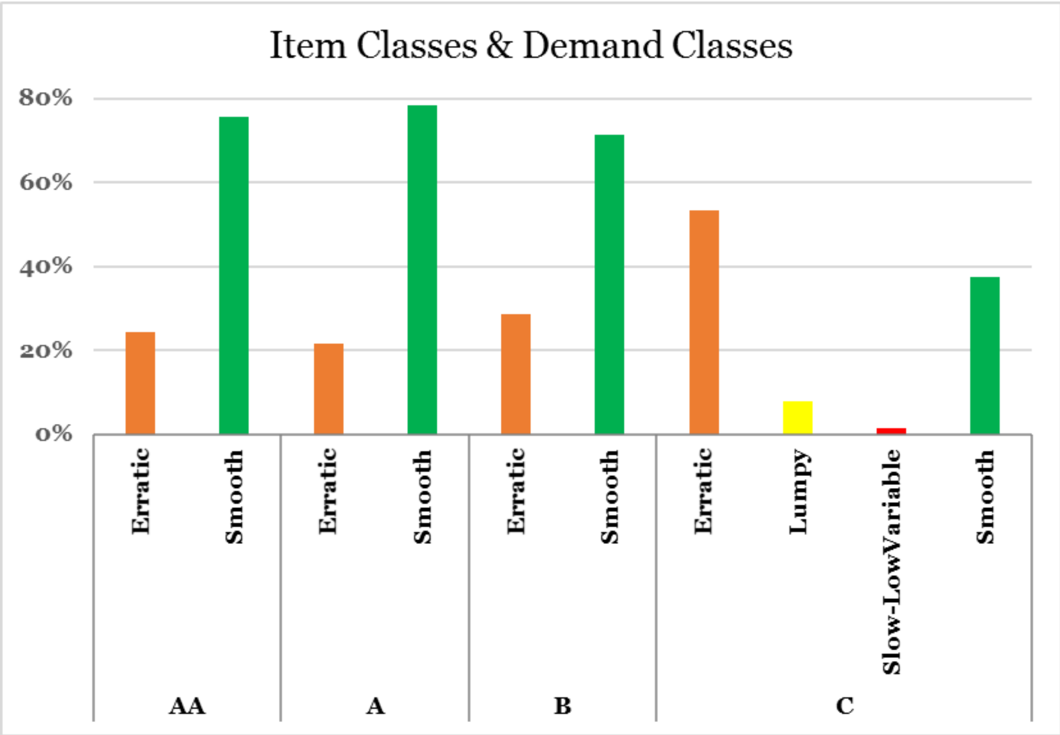



Figure 26: Demand Analysis Output [weekly buckets]: Demand Classes and Item Classes

Specifically over half of total items present a smooth demand pattern, characterized by non-intermittency and low variation in terms of quantity, fitting a normal distribution.

The second main class that gathers 40% of total items is erratic, which outlines that these items present a relatively high quantity variability along time. Specifically, the safety stock allocation problem will consider erratic demand, by assuming a non-normal lead time demand distribution in the calculation of safety stocks, and for these items significant findings and variations from the existing optimization model output may emerge.

Non-intermittent demand is captured in some C-class items only and this could be explained by the fact that C-class items are the ones with lower demand volumes shipped from the pilot hub and the ones that are requested less frequently by the market.

As a proof of the weekly demand phasing significance, demand analysis has been run on monthly basis too to confirm that, pooling demand quantity in longer time buckets, the analysis output would capture less quantity variation and categorize more product demands as normally distributed.

### 5.2.2 Safety Stock Optimization

A preliminary comparison has considered the optimal safety stock level defined by Supply Chain Guru and the actual safety stock level. To allow this, as service level to enter in the optimization model, the actual item fill rate referred to the pilot regional warehouse in the considered period has been assumed.

First, historical data about stock level in the pilot hub have been extracted for each considered item. Secondly, since the actual stock level resulted the sum of cycle stock and safety stock, it was necessary to calculate the actual cycle stock in the reference year. Cycle stock ($CS$) are determined as follows:

$$CS = \frac{Q}{2}$$

Where $Q$ is the average replenishment quantity.

To determine the cycle stock level in the reference year, the data regarding the actual inbound volumes of each item in the considered hub have been extracted. For each item, the sum of replenished quantity and the occurrence of the replenishments (the number of inbound shipments of the given site) have been calculated. The extracted data have been extracted and calculated, using boxes as unit of measure, since it was the same utilized in Supply Chain Guru model.

The actual cycle stock level has been determined as the ratio between the total inbound volumes and the number of replenishments, divided by 2, as showed in the following equation:

$$CS_{i,T} = \left(\frac{Total\ inbound\ volumes_{i,T}}{Number\ of\ actual\ replenishments_{i,T}}\right) \times \frac{1}{2}$$

Subtracting the actual cycle stock level ($CS_{i,T}$) from the actual stock level ($Tot\ S_{i,T}$), the actual average safety stock level in quantity ($SS_{i,T}$) is given.

$$SS_{i,T} = Tot\ S_{i,T} - CS_{i,T}$$

For comparison-purposes, it was necessary to convert of safety stock quantity into days of stock, since the stock level in the regional warehouses are expressed in days of stock (DOS) in Barilla inventory planning system. The actual days of safety stock ($SS\ DOS_i$) has been determined dividing the average safety stock quantity by the average daily stock consumption of the given item in the considered hub. This value has been calculated dividing the total item demand allocated to the considered regional warehouse by the total number of working days in the given period.

$$SS\ DOS_i = \frac{SS_{i,T}}{Average\ Daily\ Consumption_{i,T}}$$

The relation of the model actual days of safety stock with the actual days of safety stock revealed that the model provides a stock level on average lower than the actual level. The reasons behind the difference are to be retrieved in those effects that affect stock level and that either are not included in the current model or that are difficult to be considered in optimization modelling. Specifically the causes that may explain the difference are:

a. The actual stock level is a result of demand forecasting and forecasting error, while the model stock level output is founded on the inputted historical demand and its variability only.
b. Replenishment delays and anticipations lead to respectively lower and raise the expected stock level in a given time period.
c. The push effect, caused by anticipating some item volumes shipments with the objective to maximize the transportation mean saturation and minimize transportation costs.

d. The inventory adjustments due to demand over forecasting are product quantities stored at the regional warehouse for covering a certain forecast demand, which resulted overestimated compared to the actual one.
e. The effect of customer returned goods implies that customer may decline delivered products some specific reasons and this quantity is stocked in the regional warehouse closest to the customer.

While points (b), (c), (d), (e) are those factors related to the operating activities in the distribution and inventory system that are not possible to be modelled in a theoretical framework such as safety stock optimization model, point (a) underlines the misalignment of the stock calculation methodology between the two stock values in analysis. Indeed, being that the applied Supply Chain Guru safety stock optimization assesses the optimal stock level considering the historical demand as input information, its results cannot be evaluated compared to the actual stock level, which is based on forecast demand values.

The asymmetry of input data nature between the two methodologies used for determining the safety stock level (the actual level determined by demand forecast, while the model output based on historical demand) captures the impossibility for the evaluation of Supply Chain Guru model results at this project phase.

A second comparison carried out for the study of the model results has considered the existing safety stock optimization model output with Supply Chain Guru model result. To allow the comparison, the service level entered in Supply Chain Guru model has been the same as the target service level assumed in the existing single-echelon safety stock model. The service level measurement is common to both optimization models: item fill rate has been adopted in both cases, allowing the alignment of the optimization models in terms of service requirement parameter.

This relation between two theoretical and optimized values could result more appropriate, given that the values are not altered by operating factors, retrieved in the determination of actual stock level. Nonetheless, the input data for assessing the optimal safety stock levels differ between the single-echelon-based methodology and the multi-echelon-based one. Indeed, the asymmetry between the demand input information still remains: the current optimization model considers a forecast demand, while Supply Chain Guru optimization model has been applied with the historical demand as input data.

The absence of a benchmark appropriately aligned in terms of input data with the applied Supply Chain Guru model output, led to the impossibility to carry out an objective and structured quantitative result analysis in this phase of the project. Indeed, the very next step for a quantitative evaluation of the multi-echelon safety stock optimization results is to enter forecast demand as input data. When the application of Supply Chain Guru model integrates the forecast demand and forecasting error as variables for the determination of optimal safety stock level, the result analysis will consider its output with the optimal safety stock values being both based on forecast demand information.

From the as-is application of a multi-echelon safety stock optimization model on Barilla distribution network, some considerations that may be assumed as true are qualitative premises only.

First, the new approach assumes a holistic supply chain perspective in the analysis, recognizing the interdependence of some variables performances (such as inventory holding costs and service level) between two sites located at different echelons in the system and allocating the optimal level of stock avoiding redundant quantities. Differently, the currently implemented model in Barilla is an optimization method that allocates a specific safety stock level, that is the optimal quantity given the site-specific parameters, but it is not necessarily optimal for the whole distribution network.

Second, demand analysis tool represents an additional strength of the multi-echelon safety stock optimization model, which integrates the understanding of demand patterns for enabling an appropriate stock allocation, considering intermittency and variation of demand. This functionality allows to not assume that all item demands are normally distributed, but it captures the demand characteristics (intermittency and quantity variation) that should be considered in the safety stock allocation problem. The application of demand analysis on the historical demand series entered in the model, showed that the pilot regional warehouse handles mostly with non-intermittent-demand items, which result less difficult to manage in the inventory control and planning, compared to intermittent-demand. Nonetheless, more than one third of items emerge as erratic items, characterized by high occurrence in a given period and relatively high quantity variability. These findings about demand patterns are taken into account in the lead time demand distribution, an input variable in the assessment of optimal safety stock level. Thus, a future entry of demand forecast in the model will imply the analysis of forecast demand, as it has been applied to historical demand, providing significant demand-specific outcomes to be used as input parameters in the inventory optimization.

Beside the structural optimization model potentials, also the adopted working tool represents a key resource for future developments of the safety stock optimization process in Barilla supply chain planning system. Indeed, the application of Supply Chain Guru Safety Stock Optimization (SSO), if assessed as valid and beneficial methodology for Barilla inventory planning system, may be significant for carrying out operating tasks in the inventory planning process with enhanced flexibility, given the solvers performing both dynamic programming and linear programming for the problem resolution.

Moreover, the model scaling opportunity for future project upgrading, such as the inclusion of the whole Barilla secondary distribution network in the optimization, is a key strength to consider for the model evaluation. The operating role potentially covered by the new optimization model may be combined with a strategic function: the tool structure enables what-if analysis concerning the inventory network and it could be utilized in strategic studies concerning Barilla supply chain in an integrated way with other applied network optimization models.

# CHAPTER 6
# CONCLUSIONS AND NEXT STEPS

The application of a multi-echelon safety stock optimization model on Barilla distribution network has been initiated during this year in the Supply Chain Network Design unit, through a pilot modelling on one regional warehouse.

Being a pilot model concerning the application of an inventory optimization model with a new tool, most of the project development has dealt with the acquaintance with the software logic and with the model construction. A satisfactory model building has been achieved, putting the basis for the next steps of the project for the final definition of a safety stock optimization model as it is expected to work.

Next steps will imply the forecast demand data entry in the model, so that the optimization model is definitely provided with the appropriate input data for its real utilization. With the objective to evaluate its results in a quantitative way, the target service level to enter in the optimization model is the same as the service level utilized in the existing safety stock optimization methodology. This will ensure symmetric input data between the two models, allowing an objective and valid methodology for a quantitative result analysis. If the model will be validated, further project developments will imply its application to all seven regional warehouses in Italy and afterwards to the four Barilla depots in Europe. The model is expected to meet the operating needs in the allocation of safety stock throughout

Barilla distribution network, and if the validated model works on the whole distribution network (considering either Italian distribution network, or European distribution network) it would be exploited for what-if analysis concerning Barilla supply chain network for strategic studies.

# Bibliography

Bartezzaghi, E., Verganti, R. & Zotteri, G. (1999). Measuring the impact of asymmetric demand distributions on inventories. *International Journal of Production Economics*, 60 (1), pp 395-404.

Eaves, A.H.C. and Kingsman, B.G. (2004). Forecasting for the ordering and stock-holding of spare parts, *Journal of the Operational Research Society*, 55 (4), pp 431-437.

Eruguz, A.S., (2014). Contributions to the multi-echelon inventory optimisation problem using the guaranteed-service model approach. Other. Ecole Centrale Paris.

Fisher, M., (1997). What is the Right Supply Chain for your Product? Harvard Business Review, 75/2: 105-116.

Graves, S.C. and Willems, S.P., (2000). Optimizing strategic safety stock placement in supply chains. *Manufacturing & Service Operations Management*, 2(1), pp.68–83.

Graves, S.C. and Willems, S.P., (2008). Strategic inventory placement in supply chains: Nonstationary demand. *Manufacturing & Service Operations Management*, 10(2), pp.278–287.

Humair, S., Ruark, J.D., Tomlin, B. and Willems, S.P., (2013). Incorporating stochastic lead times into the guaranteed service model of safety stock optimization. *Interfaces*, 43(5), pp.421-434.

Inderfurth, K., (1993). Valuation of leadtime reduction in multi-stage production systems. In P.D.G. Fandel, P.D.T. Gulledge, and D. A. Jones, eds. *Operations*

*Research in Production Planning and Control*. Springer Berlin Heidelberg, pp.413–427.

Klosterhalfen, S., (2010). *Multiple sourcing in single- and multi-echelon inventory systems*. Thesis (PhD). Mannheim, Germany: University of Mannheim.

Lee, H.L., (2002). Aligning Supply Chain Strategies with Product Uncertainties. *California Management Review*, 44(3): 105-119.

Minner, S., (2000). *Strategic safety stocks in supply chains*, Springer Berlin Heidelberg.

Neale, J.J. and Willems, S.P., (2009). Managing inventory in supply chains with nonstationary demand. *Interfaces*, 39, pp.388–399.

Perego, A., *Inventory Planning*. Retrieved from Logistics Management Course (2017-18). Politecnico di Milano.

Rambau, J. and Schade, K., (2010). The stochastic guaranteed service model with recourse for multi-echelon warehouse management. *Electronic Notes in Discrete Mathematics*, 36, pp.783-790.

Silver, E.A., Pyke, D.F. and Peterson, R., (1998). *Inventory management and production planning and scheduling*, Hoboken, New Jersey: John Wiley & Sons.

Simchi-Levi, D. and Zhao, Y., (2012). Performance evaluation of stochastic multi-echelon inventory systems: A survey. *Advances in Operations Research*, 2012, pp.1–34.

Simpson, K.F., (1958). In-process inventories. *Operations Research*, 6(6), pp.863–873.

Syntetos, A.A., Boylan, J.E. & Croston, J.D. (2005). On the categorization of demand patterns. *Journal of the Operational Research Society*, 56 (5), pp 495-503.

Syntetos, A.A., Boylan, J.E. (2005). The accuracy of intermittent demand estimates. *International Journal of Forecasting*, 21 (2), pp 303-314.

Willems, S.P., (2008). Data set—Real-world multi-echelon supply chains used for inventory optimization. *Manufacturing & Service Operations Management*, 10(1), pp.19–23.

Zotteri, G. (2000). The impact of distributions of uncertain lumpy demand on inventories. *Production Planning & Control*, 11 (1), pp 32-43.

Zipkin, P.H., (2000). *Foundations of Inventory Management*, Singapore: McGraw-Hill.

Il Sole 24ore, (2017): *Alimentare, 2017 record per le esportazioni italiane*, December 20. Retrieved from: http://www.ilsole24ore.com/art/notizie/2017-12-20/alimentare-2017-record-storico-le-esportazioni-italiane--161420.shtml

ISMEA, (2015): *L'industria Pastaria. Piani di settore.*

Learningcenter.Llamasoft.com.(https://learningcenter.llamasoft.com/wp-content/helpfiles/SupplyChainGuruDotCom/WebHelp/index.htm#SCGCOM_UI/Using_SafetyStockOptimization/Using_SafetyStockOptimization.htm)