UNIVERSITÀ della CALABRIA
Facoltà di Ingegneria
Dipartimento di Meccanica

Scuola di Dottorato "Pitagora" in Scienze Ingegneristiche

Dottorato di Ricerca in Ingegneria Meccanica XXII Ciclo

SETTORE SCIENTIFICO DISCIPLINARE: ING-IND/17

Tesi di Dottorato

Inventory and Warehouse Management in Production Systems and Supply Chain based on advanced Modeling & Simulation

Coordinatore
Prof. Sergio Rizzuti

Supervisore
Prof. Giovanni Mirabelli

Candidato
Ing. Duilio Curcio

Dissertazione finale sottomessa per ottenere il titolo di Dottore di Ricerca in Ingegneria Meccanica

Anno Accademico 2008/2009

Table of Contents

List of Figures

List of Tables

Introduction

This Thesis presents the results of the activities carried out during the three years PhD course at the Mechanical Department of the University of Calabria (Italy), Industrial Engineering Section. The PhD course focuses on the Inventory and Warehouse Management problem in Production Systems and Supply Chain by using advanced investigation approaches based on Modeling & Simulation.

The first step of the PhD course was to correctly define the research area: after an initial pre-screening of the literature and according to the ongoing research activities at the Modeling & Simulation Center – Laboratory of Enterprise Solutions (*MSC-LES*, at Mechanical Department of University of Calabria) it was decided to focus on two specific and related issues: the Inventory Management problems (definition, testing and comparison of new inventory control policies) and the Warehouse Management problem (warehouse resources allocation for improving warehouse internal efficiency and service level provided upstream and downstream the supply chain).

The PhD course has been subdivided into three parts: review of the state of the art, training activities and the research activities.

An accurate review of the state of the art was carried out in the area of Inventory and Warehouse Management: all the academic books, international journals articles and conference proceedings articles reported in the bibliography at the end of each Chapter (and cited within it) have been read, deeply analyzed and discussed. Chapter 1 provides the reader with an accurate overview on methodologies and scientific approaches proposed (during the last decades) by researchers, scientists and practitioners working in the Inventory and Warehouse Management areas. Chapter 1 passes through the description of several research works, as they run through the literature, according to the methodology or scientific approach they propose. The initial search identifies a huge number of references (about 600 references) which were reduced to about 157 references based on contents and quality (112 references cited in Chapter 1 and 45 references in the remaining chapters). The descriptive analysis of the literature reveals heterogeneity among the scientific approaches due to the different models, techniques and methods adopted for facing the inventory and warehouse management problem both in manufacturing systems and in supply chains.

The main goal of training activities was twofold: (i) to learn the main principles to carry out a simulation study and (ii) to gain knowledge and experience in using different simulation software tools to develop simulation models in manufacturing and supply chain areas. Detailed studies have been made concerning simulation modeling principles, input data analysis, Verification, Validation and Accreditation (*V&VA*), simulation runs planning by using the Design of Experiments (*DOE*), simulation results analysis by using the Analysis of Variance (*ANOVA*). The software tools adopted for the implementation of simulation models and simulation results analysis are: eM-Plant™ by *Tecnomatix Technology* (a discrete event simulation software), Anylogic™ by *XJ Technologies* (a java-based simulation software), Minitab™ by *Minitab Inc.* (a specific tool for statistical analysis), C++, Simple ++ and Java (general purpose and specific programming languages for simulation models development). The training activity has been carried out at University of Calabria (*MSC-LES*, Industrial Engineering Section) and at General Electric, Oil & Gas Section (*Nuovo Pignone S.p.A* plant located in Vibo Valentia, Italy). The results of the training part are presented and discussed in Chapter 2. Indeed Chapter 2 presents two applications examples (in two different areas, manufacturing and supply chain) with the aim of facing the main problems and critical issues in developing a simulation study. The application examples developed in this part were useful to gain confidence with simulation and statistic software as well as they also propose (i) an advanced modeling approach for developing flexible and time efficient simulation models and (ii) the integration of two different artificial intelligence techniques (Ants Theory and Genetic Algorithms) with one of the simulation models proposed in the application examples. Note that the application examples proposed in Chapter 2 are not part of the research activities in the area of Inventory and Warehouse Management; as already mentioned the main goal of the training part was to acquire knowledge and experience in developing simulation models.

The main results of the research activity are presented in Chapters 3 and 4 respectively for the Inventory Management and Warehouse Management.

Chapter 3 proposes and defines six new inventory control policies. For each inventory control policy a mathematical model is presented. To provide relevance on the potentials of the inventory control policies proposed, their behaviors and performances have been tested and compared in two different real contexts: a manufacturing system devoted to produce high pressure hydraulic hoses and a three echelons supply chain operating in the beverage sector. In both cases an advanced simulation model is used for investigating and comparing inventory control policies behavior under different constraints in terms of demand intensity, demand variability and lead times.

In Chapter 4, after an introduction on the role of warehouses in logistic systems, the warehouse management problem is faced from the point of view of optimal warehouse resources allocations and internal logistics costs reduction. The main goal of the research is to understand how different warehouse resources allocations affect both the internal warehouse efficiency and the service level provided upstream (*suppliers*) and downstream (*retailers*) the supply chain. To this end a simulation model of a real warehouse supporting the large scale retail sector is presented. The first analysis, carried out by using the simulation model, considers the effects of resources allocation on the average number of handled packages per day and on the average daily cost for each handled package. The second analysis evaluates the analytical relationship between some critical parameters (the number of suppliers' and retailers' trucks per day, the number of forklifts and lift trucks, the number of warehouse shelves levels) and the service level provided to suppliers and retailers (in terms of waiting time of suppliers' trucks before starting unloading operations and waiting time of retailers' trucks before starting loading operations).

The research activities proposed in Chapters 3 and 4 has been developed at University of Calabria (*MSC-LES*, Industrial Engineering Section, Italy), at University of Genoa (Savona Campus, *DIPTEM* and *Simulation Team*, Italy) and at General Electric, GE Oil & Gas (*Nuovo Pignone S.p.A* plant, Vibo Valentia, Italy).

CHAPTER 1

Inventory and Warehouse Management: the state of art overview

1.1 Introduction on Inventory Management

According to Simchi-Levi *et al.* (2007), a Supply Chain (*SC*) is a network of different entities or nodes (industrial plants, distribution centers (*DCs*), warehouses and retailers) that provide materials, transform them in intermediate or finished products and deliver them to customers to satisfy market requests.

For characterizing each SC node, two different parameters have to be introduced:

- the *demand*;
- the *productive capacity*.

The definition of these parameters usually requires a huge effort in terms of data collection.

In effect, the information management related to demand and productive capacity is a very complex task characterized by a great number of critical issues related to:

- market needs (*volumes* and *production ranges*);
- industrial processes (*machines downtimes*, *transportation modes*);
- supplies (*parts quality*, *delivery schedules*).

The market demand and the productive capacity also generate a flow of items and finances towards and from the SC node. Needless to say, the Supply Chain Management (*SCM*) takes care of the above-mentioned issues, studying and optimizing the flow of material, information and finances along the entire SC. In fact, the main goal of a SC manager is to guarantee the correct flows of goods, information and finances throughout the SC nodes for assuring the right goods in the right place and at the right time. Among others, the inventory management problem along the SC plays a critical role because it strongly affects the SC performances. Lee and Billington (1993) consider the inventory control as the only tool to protect SC stability and robustness. Longo and Ören (2008) also assert that an efficient inventory management along the SC positively affects the SC resilience. In effect, the objective of the Supply Chain Inventory Management (*SCIM*) is to satisfy the ultimate customer demand increasing quality and service level and decreasing, at the same time, total costs; inventories affect SC costs and performance in terms of:

- values tied up, e.g., raw materials have a lower value than finished products;
- degrees of flexibility, e.g., raw materials have higher flexibility than finished products because they can be easily adopted for different production processes;
- levels of responsiveness, e.g., in some cases products delivery could be made without strict lead times whereas raw materials transformation usually requires stringent lead times.

1.2 The Inventory Management problem

According to Bassin (1990), an efficient inventory control plays a key-role in the management of each company. In fact, many companies reducing their investments in fixed assets (i.e. plants, warehouses, equipment and machinery) aim also at reducing inventories (Coyle *et al.*, 2003). In particular, wholesalers and retailers have to solve the inventory management problem by keeping inventory at reasonable levels due to the difficulty of demand forecasting and customers' expectations about products availability (Coyle *et al.*, 2003).

The difficulty of demand forecasting lead to two opposite issues: the inventory *over-stock* and *stock-out*. In fact, trying to avoid lost sales caused by inventory stock-outs, companies demonstrate a tendency to overstock; from the other side, because of the fact that keeping inventory is costly, companies reduce the inventory level, so the tendency to inventory stock-out is evident. Coyle *et al.* (2003) argue about the effects of stock-out while Toomey (2000) discusses about the reasons for setting safety stocks. Goldsby *et al.* (2005) introduce a new parameter to monitor the inventory levels of a company. This parameter is represented by the *inventory turns* which can be expressed mathematically as the ratio between the sales volume at cost and the value of average inventory.

As a matter of fact, the Inventory Management problem must address two critical questions:

- time for ordering;
- quantities to be ordered.

According to Minner (2000), addressing correctly such issues also depends on transaction, safety and speculation. The transaction is the result of the fact that ordering and manufacturing decisions are made at certain points of time instead of being performed continuously; the safety emerges in uncertainty situations where lead-time, demand and production are unknown at the time of decisions; the speculation is generally related to prices uncertainty.

Furthermore, Minner (2000), groups inventories into:

- *cycle stocks*: the cycle stock is induced by batching and changes between an upper level (when a batch has just arrived) and a lower level (just before the arrival of the next batch);
- *pipeline stocks*: order processing times, production, transportation rates contribute to pipeline stocks, also called *process inventories*. Material that are in process, in transport, and in transit to another processing unit belong to pipeline stocks;
- *safety stocks*: the safety stock can be considered as the expected inventory just before the next replenishment arrives and it is caused by the uncertainty of demand, processing time, production and other factors;
- *speculative stocks*: they are generated by earlier supplies due to expected price increase or by possible higher selling prices;
- *anticipation stocks*: anticipation stocks are related to products with seasonal demand.

In function of the classification above mentioned, it is difficult to identify to which of the categories a certain item belongs because of stocks can be originated from more than a single inventory control.

1.3 The Inventory Control Systems

According to Silver *et al.* (1998), an inventory control system has to solve the following three issues:

- how often the inventory status should be determined;
- when a replenishment order should be placed;
- how large the replenishment order should be.

These issues become easy to solve under conditions of deterministic demand, but the answers are more difficult to obtain under probabilistic demand.

Literature proposes many inventory control systems and control policies. Most of them deal with some complex mathematical model (Lin, 1980). In the following Sections, the most important inventory control systems are introduced.

1.3.1 The ABC classification

According to Silver *et al.* (1998), the ABC analysis is an important tool which help company managers to establish how critical the item under consideration is to the firm. It is an inventory classification technique in which the items in inventory are classified according to the dollar volume (value) generated in annual sales (Fuerst, 1981). Onwubolu and Dube (2006) assert that only the application of the ABC analysis to an inventory situation determines the importance of items and the level of control placed on the items. Furthermore, the A items represent about the 20 percent of the total number of items and the 80 percent of the dollar sales volume; B items are roughly 30 percent of the items, but represent 15 percent of the dollar volume; C items comprise roughly 50 percent of the items, and represent only 5 percent of the dollar volume. Slow-moving and inexpensive items critical to the company are also included among the A items.

1.3.2 Continuous and periodic review

Once the importance of an item is determined, the next step is to define a control system or policy to monitor inventory status, place replenishment orders for items, decide the amount to be ordered. In the next Section, continuous and periodic review control policies are presented.

Two review approaches can be adopted: the *continuous* review and the *periodic* review. In the first case, the stock status is always known. In reality, the continuous review is generally not required because in correspondence of each order an immediate updating of the inventory status is made. From the other side, the periodic review implies a definition of the stock status only every R time units, where R is the review interval which is the time that elapses between two consecutive moments at which the stock level is known.

The periodic review system has the advantage to allow a significant prediction of the workload level of the staff involved. From the other side, the continuous review is generally more expensive in terms of reviewing costs and reviewing errors than the periodic review, e.g. fast-moving items where there are many transactions per unit of time. On the other hand, periodic review is more effective than continuous review in detecting spoilage (or pilferage) of such slow-moving items. Taking into consideration the customer service level, the continuous review has the advantage to guarantee the same service level with less safety stock than the periodic review because in the case of the periodic review a greater safety protection is needed in order to prevent unexpected reductions of the stock level.

As already mentioned, according to the Supply Chain Inventory Management (*SCIM*) principles, the objective of an inventory control system is twofold:

- evaluation of the time for purchasing order emission;
- evaluation of the quantity to be ordered.

In the following, four classical inventory control policies are described. These policies are:

1. the Re-Order-Point, Order Quantity *(s, Q)* policy;
2. the Periodic-Review, Order-Up-To-Level *(R, S)* policy;
3. the Order-Point, Order-Up-To-level (*s*, *S*) policy;
4. the (*R*, *s*, *S*) policy.

The parameter to take into consideration is the Inventory Position (*IP*) defined as the on-hand inventory plus the quantity already on order minus the quantity to be shipped. According to Sylver *et al.* (1998), this parameter has an important role because it includes not the net stock, but the on-order stock, takes into account all the material ordered but not yet received from the supplier.

In fact, if the net stock is the parameter chosen for deciding when an order should be submitted, unnecessarily another order might be placed today even though a large shipment was due in tomorrow.

Next Section presents the mathematical formulation for each policy.

1.3.3 The Re-Order-Point, Order-Quantity *(s, Q)* policy

This is a continuous review system (R = 0).

A fixed quantity *Q* is ordered whenever the inventory position drops to the reorder point *s* or lower. Note that the inventory position, and not the net stock, is used to trigger an order.

The quantity to be ordered can be defined using the Economic Order Quantity (*EOQ)* approach.

This control policy is also defined as a *two-bin policy*: there are two bins for storage of an item. Demand is initially satisfied from the first bin; when it is used up the second bin is opened so an order is made out for replenishment (the items in the second bin represents the reorder point). When the replenishment arrives, the second bin is refilled and the items been left are put into the first bin. It is important to underline that this system works well when no more than one replenishment order is placed.

The advantages of this policy are:

- it is simple to adopt, especially in the two-bin form;
- errors are less likely to occur;
- predictable production requirements for the supplier.

From the other side, the most important disadvantage is related to the incapability, in case of large transactions, to guarantee a quantity large enough to raise the inventory position above the reorder point.

1.3.4 The Periodic-Review, Order-Up-To-Level *(R, S)* policy

Unlike the previous control policy, the Periodic-Review, Order-Up-To-Level *(R,S)* policy, also known as a *replenishment cycle* policy, is based on a periodic check, see Figure 1.1. If *R* is the review period, every *R* units of time, the quantity to order is defined by *S(t)* minus *IP(t)*.

The value of *R* can be defined using the inverse formula usually used for evaluating the EOQ. In this policy, *S(t)* represents the target level. This policy should be used when:

- inventory level is not automatically monitored;
- there are advantages related to scale economy;
- orders are not regular.

Because of its properties, this policy is more adopted than the Re-Order-Point, Order-Quantity policy because of a simple coordination of the replenishments, e.g. the coordination guaranteed by this policy becomes very important in terms of savings if consider that, in case of orders from overseas, in order to keep shipping costs under control, generally a shipping container is filled. This policy has the main disadvantage that the carrying costs are higher than in continuous review systems.

1.3.5 The Order-Point, Order-Up-To-Level (s, S) policy

This policy can be derived from the previous policies above mentioned. Like the Re-Order-Point, Order-Quantity policy, a replenishment is made whenever the *IP(t)* equals or is lower than the re-order point, see Figure 1.2.

From the other side, this policy differs from the Re-Order-Point, Order-Quantity policy because, for increasing the *IP(t)* to the target level, a variable quantity is anyway ordered.

According to literature, there are two parameters which characterize this policy:

- *s (t)*, the re-order level at time t;
- *S(t)*, the order-up-to-level or target level at time t.

This policy is also defined as *min-max system* because the inventory position, with the exception of some particular cases, is included between the minimum value (the *order-point*) and a maximum value (the *target level*). Moreover, according to Sylver *et al.* (1998), the total costs of replenishment, carrying inventory and shortage are comparable to the costs of the reorder point-order quantity policy.

1.3.6 The (*R*, *s*, *S*) policy

This inventory management policy can be considered a combination of the *(s, S)* and *(R, S)* policies. A check on the inventory position is made every *R* units of time. If it is at or below the reorder point *s*, an order enough to raise it to *S* is produced. If the position is above *s*, nothing is done until the next review.

Moreover, the *(s, S)* policy is the special case where *R = 0* and the *(R, S)* is the special case where *s = S-1*. From the other side, the *(R, s, S)* policy can be considered as a periodic version of the *(s, S)* policy and the *(R, S)* situation can be viewed as a periodic implementation of *(s, S)* with *s = S-1*.

Scarf (1960) asserts that, under quite general assumptions about the demand pattern and the cost factors involved, the *(R, s, S)* policy generates lower total replenishment, carrying, and shortage costs than any other inventory control methodologies. However, this policy needs a heavy computational effort because three control parameters have to be evaluated.

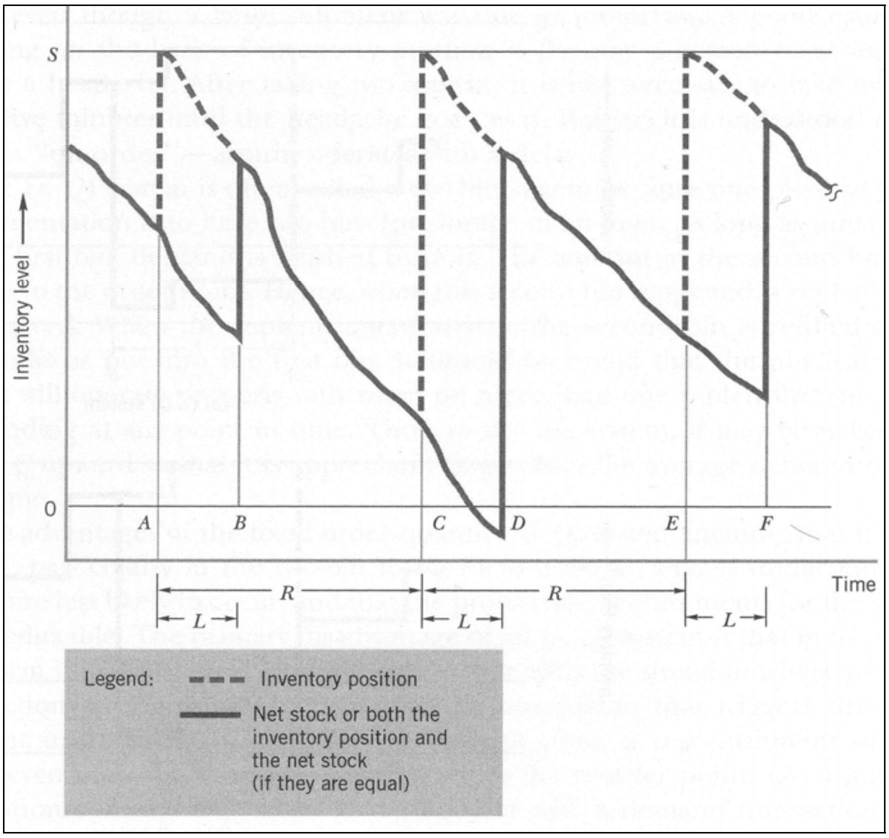


Figure 1.1 – The *(R,S)* policy (Source: Sylver *et al.* (1998))

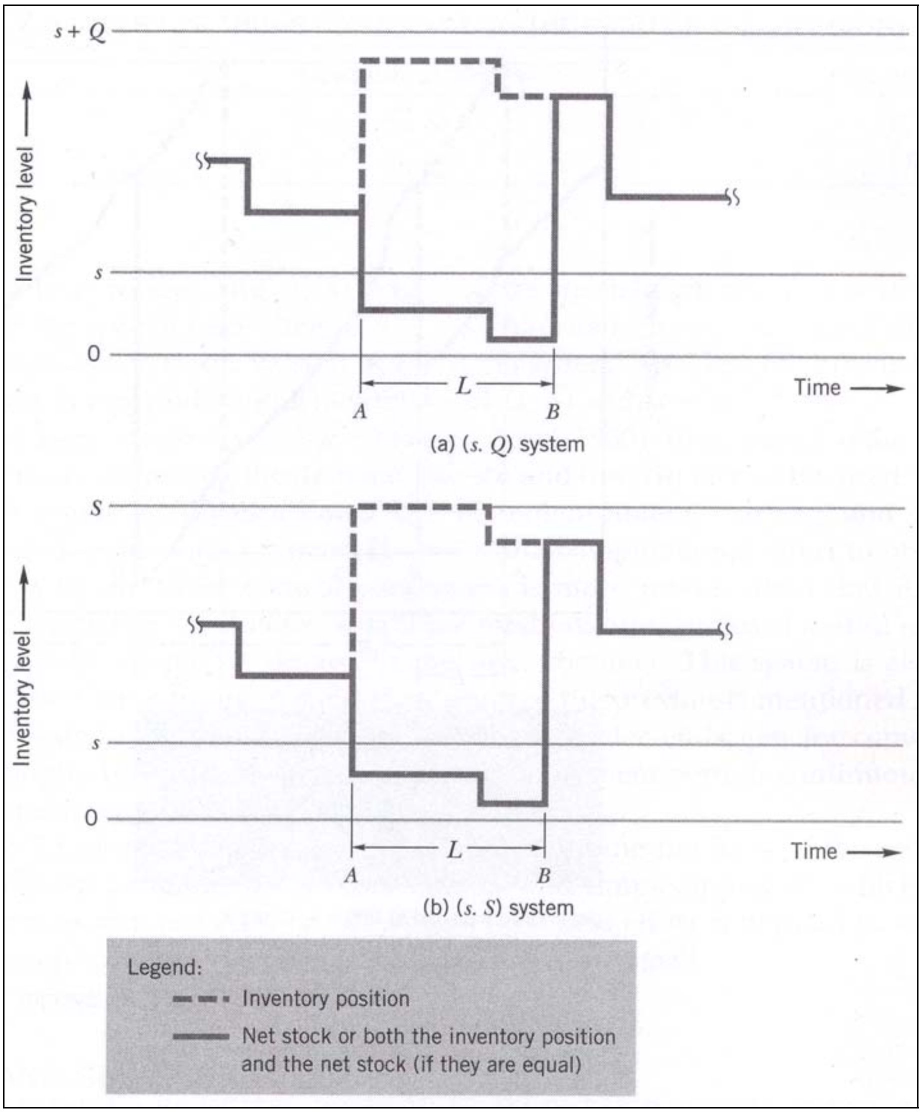


Figure 1.2 – The *(s,S)* policy (Source: Sylver *et al.* (1998))

1.4 Inventory management research studies

In recent years, a great number of research studies on SCIM have been proposed. In particular, these research studies concern to:

- *Analytical models for inventory management.* D'Esopo (1968) proposes a review of the re-order point order-quantity policy introducing a new time parameter, the expedited lead time, lower than the normal procurement lead time. Ramasesh *et al.* (1991) propose a variant of the same policy with parameters related to demand variability and lead times to minimize total purchasing, delivery and inventory costs. Cormier and Gunn (1996) discuss about cost models for inventory and inventory sizing models. Minner *et al.* (1999) consider an analytical model of a two-echelon system in which parameters related to outstanding orders are introduced; Minner (2003) provides a review on Inventory Models (*IMs*) and addresses their contribution to SC performance analysis.

- *Constrained inventory management systems*. Inderfurth and Minner (1998) investigate an analytical model to determine safety stocks considering as constraint different service levels; Chen and Krass (2001) propose a new inventory approach, based on the minimal service-level constraint, which consists in achieving a minimum defined service level in each period; Huang *et al.* (2005) study the impact of the delivery mode on a one-warehouse multi-retailer system to evaluate the optimal inventory ordering time and the economic lot size for reducing total inventory costs; De Sensi *et al.* (2008) propose the analysis of different inventory control policies under demand patterns and lead time constraints in a real SC; Longo and Mirabelli (2008) analyze the effects of inventory control policies, lead times, customers' demand intensity and variability on three different SC performance measures.
- *Inventory management and parameters variability.* Moinzadeh and Nahmias (1988) analyze an extension of the classical (s,Q) policy; Moinzadeh and Schmid (1991) study a one-for-one ordering policy introducing parameters related to net inventory and the timing of all outstanding orders; Qi *et al.* (2004) analyze deviation costs of one supplier-one retailer system after demand disruption; Zhou *et al.* (2007) introduce an algorithm to compute the parameters of a single item-periodic review inventory policy.
- *Inventory management and SC configurations (single/multi-echelon systems)*. Moinzadeh and Aggarwal (1997) study a multi-echelon system incorporating the emergency ordering mechanism; Ganeshan (1999) studies a continuous-review, one-warehouse, multiple-retailer distribution system; Dellaert and De Kok (2004) present an integrated approach for resource, production and inventory management of an assembly system; Chen and Lee (2004) implement an analytical model for demand variability, delivery modes, inventory level and total costs in a multi-echelon SC network.
- *Modelling and simulation for inventory management along the Supply Chain.* The evaluation of the performances of different entities involved in the SC, from suppliers to final customers passing through DC, involves a number of stochastic variables and parameters and is a quite complex task in which analytical models often fall short of results applicability. The literature analysis show that the Modeling & Simulation (*M&S*) approach is able to recreate the whole complexity

of a real supply chain. Bhaskaran (1998) carries out a simulation analysis of SC instability and inventory related to a manufacturing plant: in this case, simulation is used in combination with artificial intelligence techniques (i.e., fuzzy theory and genetic algorithms) for a better understanding of the effects of different inventory strategies on the SC structure and for supporting the decision-making process. Giannoccaro and Pontrandolfo (2002) propose an artificial intelligence algorithm to manage inventory decisions at all SC stages (optimizing the performance of the global SC by using a simulation approach). Huang *et al.* (2005) solve the ordering and positioning retailer inventories problem at the warehouse and stores, satisfying specific customer demand and minimizing total costs by using neural network approaches. For simulation models development, different commercial software and programming languages have been adopted: Bertazzi *et al.* (2005) implement in C++ a vendor-managed inventory policy to minimize purchasing, replenishment and delivery total costs; Lee and Wu (2006) model the reorder point-order quantity (RPOQ) and the periodic review order-up policy of a distribution system by using the commercial package eM-Plant™ while Al-Rifai and Rossetti (2007) adopt Arena™ for testing a new analytical model for a two-echelon inventory system.

1.5 Introduction on Warehouse Management

Warehouses are usually large plain buildings used by exporters, importers, wholesalers, manufacturers for goods storage. Warehouses are equipped with loading docks to load and unload trucks, cranes and forklifts for moving goods, as shown in Figure 1.3.

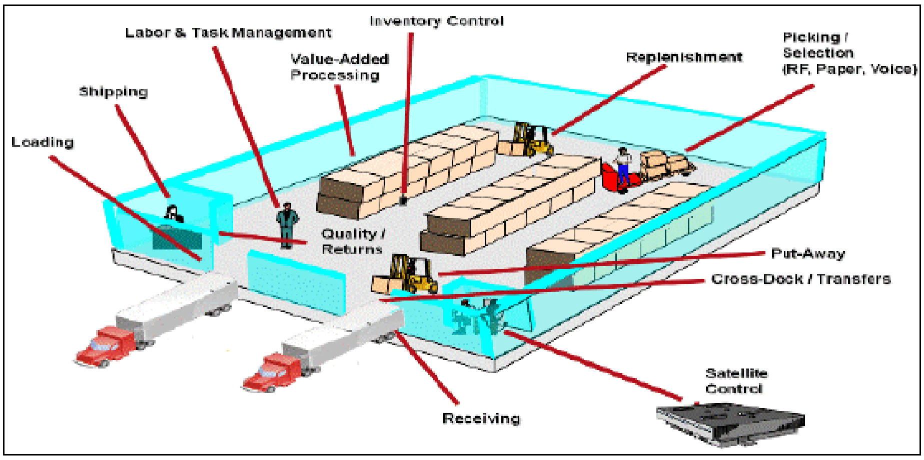


Figure 1.3 – The Warehouse Layout (Source: Rajuldevi *et al.* (2009))

Some warehouses are fully automated, i.e. products are moved from one place to another by automated conveyors and automated storage and retrieval machines which run by programmable logic controllers and also with logistics automation software (Eben-Chaime and Pliskin, 1997). This kind of warehouses are characterized by a Warehouse Management System (*WMS*), a database driven computer program for the material tracking (Mason *et al.*, 2003). As a consequence, logistics experts adopt the WMS to improve the efficiency of the warehouse through an accurate control of the inventory levels.

According to Rajuldevi *et al.* (2009), during the last years Just in Time (*JIT*) techniques designed to enhance the return on investment (*ROI*) of a business by reducing in-process inventory cause some changes in the traditional warehousing. JIT is based on delivering products directly from manufacturing plants to retailers without using warehouses, but, because of the distance between manufacturers and retailers increases considerably in many regions or countries, a warehouse per region or per country for a given range of products is usually needed (Tompkins *et al.*, 1998).

Nowadays, new changes in marketing strategies are leading to the development of a new warehouse designing approach, i.e. the same warehouse is used for warehousing and also as a retail store. As a consequence, manufacturers can directly reach consumers by avoiding or by-passing importers or other middle agencies (Tompkins *et al.*, 1998).

These warehouses are equipped with tall heavy industrial racks where items ready for sale are placed in the bottom parts of the racks while the palletized and wrapped inventory items are usually placed in the top parts.

1.5.1 Warehouses classification

In function of products managed, warehouses can be classified into:

- *raw material and components warehouses*: they hold raw material and have usually the function to provide raw material to manufacturing or assembly processes;
- *work-in-process warehouses*: they hold partially completed products and assemblies at various points along production lines or assembly lines;
- *finished goods warehouses*: they are usually situated near the manufacturing plants and hold finished items;
- *distribution warehouses/distribution centers*: distribution warehouses collect products from various manufacturing points in order to combine shipments to the common customer. Normally, these

warehouses are located at a central position between the manufacturing plants and the customer;

- *fulfillment warehouses/fulfillment centers*: they receive, pick and ship small orders for individual consumers;
- *local warehouses*: they receive, pick and ship a few items to the customer every day;
- *value-added service warehouses*: in these warehouses key product customization activities take place, i.e. packaging, labeling, marking and pricing.

From a geographical point of view, warehouses can be distinguished into:

- *centralized warehouse*: all the warehousing services are concentrated to one specific warehouse unit which provides services to the whole firm. A centralized approach is characterized by a high control and efficiency of the system and improvement in productivity through balancing, but it has some limitations like high initial costs, customers' concentration in only certain market sectors, long internal transportation paths in large central warehouses and higher costs for the infrastructure, etc. (Korpela and Tuominen, 1996);
- *de-centralized warehouse*: each warehouse is autonomous and independent from its own resources without any major considerations over the remaining units of the network to which it belongs. In this approach each facility identifies its most effective strategy without considering the impact on the remaining facilities. The main characteristics of the decentralized approach are flexibility, service orientation, increase in responsiveness and they provide as good service as the centralized warehouses in terms of customer service level. Limitations are related to lack of centralized control, resources duplication and costs increase (Tompkins *et al.*, 1998; Mulcahy, 1994).

1.5.2 The warehouse functions

All the processes which take place within a warehouse are reported in Figure 1.4. These processes are:

- *receiving*: this is the setup operation for all other warehousing activities. In particular, receiving materials is a critical process within a warehouse: it will create problems in put away, storage, picking and shipping processes because if inaccurate deliveries and damaged material are allowed into the warehouse then the same have to be shipped. The receiving process can be subdivided into the following operations: direct shipping, cross-docking, receiving scheduling, pre-receiving and receipt preparation;

- *put away*: this is the inverse process of the order picking. It can be subdivided into: direct put away, directed put away, batched and sequenced put away, interleaving;
- *pallet storage*: there are different storage methodologies, i.e. block stacking, stacking frames, single-deep selective pallet rack, double-deep rack, drive-in rack, drive-through-rack, pallet flow rack, push-back rack;
- *pallet retrieval*: the most popular pallet retrieval systems are walk stackers, counterbalance lift trucks, straddle trucks, side loader trucks, hybrid trucks, automated storage and retrieval (ASR) machines;

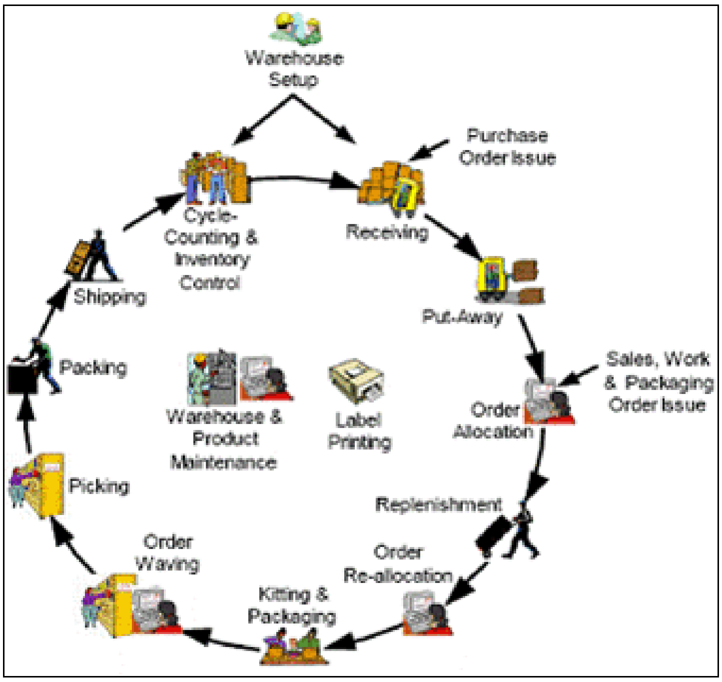


Figure 1.4 – The Warehouse Functions (Source: www.readymicrosystems.com)

- *case picking systems* which can be classified into three categories (Briggs, 1978): pick face palletizing systems, downstream palletizing systems, direct loading systems;
- *unitizing and shipping*: these activities are classified as container optimization, container loading, weight checking, automated loading, dock management (Briggs, 1978).

1.5.3 Warehousing costs

Warehousing costs can be distinguished in:

- *general overhead costs*: these costs involve the cost of the space available per cubic square meter and infrastructure and also include the cost for various security devices such as security alarms, auto IDs, etc;
- *delivery costs* are the costs incurred in the distribution of the freight by an outside vendor. These costs include the cost of fuel, insurance and the cost of the delivery trucks;
- *labour costs*: these costs involve the cost of the labour that perform various operations in the warehouse including receiving incoming goods, entering relevant data into computer systems and administrative duties.

The warehouse costs can also be classified as:

- *processing costs*: these are costs incurred by various operations and processes carried out in the warehouse such as receiving, storing, picking, packaging and shipping;
- *storage costs (handling costs)*: these are costs incurred to store and handle products and are also known as *inventory holding costs*.

1.5.4 Warehouse management research studies

This Section proposes a review of the state of art on warehouse management. According to Gu *et al.* (2007), the warehouse management problem can be tied to five major decisions as illustrated in Figure 1.5:

- defining the overall warehouse structure which consists in analyzing the material flow within the warehouse and in specifying the functional departments and their relationships;
- sizing and dimensioning the warehouse and its departments aim at defining the size and dimension of the warehouse as well as the space allocation of the various warehouse departments;
- defining the detailed layout within each department consists in the detailed configuration within a warehouse department, for example, aisle configuration in the retrieval area, pallet block-stacking pattern in the reserve storage area, and configuration of an Automated Storage/Retrieval System (*AS/RS*);
- selecting warehouse equipment means to determine an appropriate automation level for the warehouse and identify equipment types for storage, transportation, order picking and sorting;
- selecting operational strategies defines how the warehouse has to be managed, for example, with regards to storage and order picking, i.e. the choice between randomized storage or dedicated storage,

whether or not to do zone picking and the choice between sort-while-pick or sort after- pick, etc.

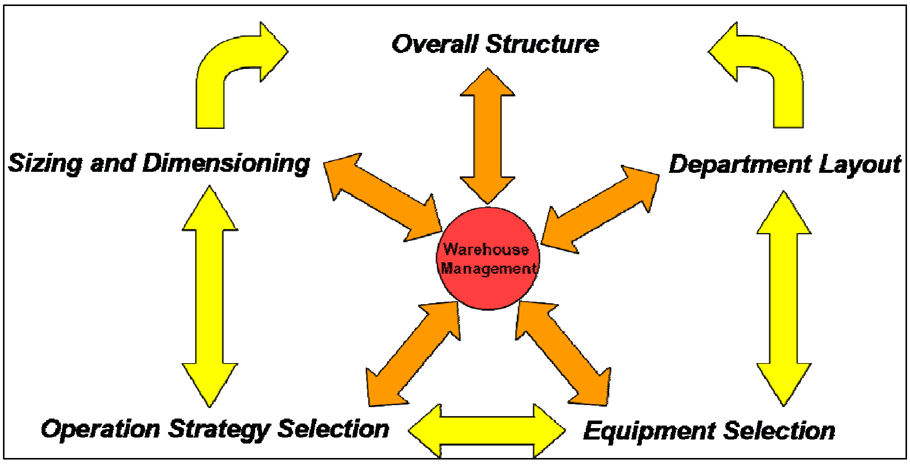


Figure 1.5 – The Warehouse Management Problem

More in detail, the definition of operational performance measures (in terms of costs, capacity, space utilization and service provided) is fundamental for evaluating the effects of specific decisions. Furthermore, efficient performance evaluation methods, i.e. benchmarking, analytical models and simulation models, can help experts to evaluate several system configurations without any considerable costs.

Different surveys on warehouse management studies are proposed by Cormier (2005), Cormier and Gunn (1992), Van den Berg (1999) and Rowenhorst *et al.* (2000).

Literature review on warehouse design can be classified into four main topics:

- warehouse design (or management);
- warehouse performance analysis;
- warehousing case studies;
- computational (or simulation) models.

Now the state of art on warehouse design and management which can be subdivided into five subsections (Figure 1.5) is provided.

1.5.5 The warehouse design and management

As before mentioned, defining the overall structure (or conceptual design) of a warehouse consists in designing the functional departments, i.e. the number of storage departments (Park and Webster, 1989; Gray *et al.*, 1992; Yoon and Sharp, 1996), technologies to adopt (Meller and Gau, 1996), personnel to engage, aiming at satisfying storage and throughput requirements and minimizing costs.

Warehouse sizing and dimensioning has important implications on construction, inventory management and material handling costs. In particular, *warehouse sizing* establishes the storage capacity of a warehouse. Two scenarios can be considered in solving the sizing problem:

- the inventory level is defined externally and, as a consequence, the warehouse has no direct control on the incoming shipments arrivals and quantities (e.g. in a third-party warehouse), but the warehouse has to satisfy all the requirements for storage space. White and Francis (1971) study this problem for a single product over a finite planning horizon taking into consideration costs related to warehouse construction, storage of products and storage demand not satisfied within the warehouse;
- the warehouse can directly control the inventory policy as in the case of an independent wholesale distributor so correct inventory policies and inventory costs should be evaluated, see Levy (1974), Rosenblatt and Roll (1988), Cormier and Gunn (1996) and Goh *et al.* (2001).

The state of art also proposes research studies with either fixed or changeable storage size (i.e. the storage size changes over the planning horizon so the decision variables are the storage sizes for each time period), as reported in Lowe *et al.* (1979), Hung and Fisk (1984) and Rao and Rao (1998).

From the other side, *warehouse dimensioning* deals with the floor space definition in order to evaluate construction and operating costs. Francis (1967) faces this problem for the first time by using a continuous approximation of the storage area without considering aisle structure; Bassan *et al.* (1980) review Francis (1967) model by considering aisle configurations; Rosenblatt and Roll (1984) integrate the optimization model in Bassan *et al.* (1980) with a simulation model which evaluates the storage shortage cost as a function of storage capacity and number of zones.

Other research studies propose a trade-off in determining the total warehouse size, allocating the warehouse space among departments, and determining the dimension of the warehouse and its departments, as reported in Pliskin and Dori (1982), Azadivar (1989) and Heragu *et al.* (2005).

Within each warehouse department, the department layout or storage problem can be classified in:

- *pallet block-stacking pattern* (storage lane depth, number of lanes for each depth, stack height, pallet placement angle with regards to the aisle, storage clearance between pallets and length and width of aisles);

- *storage department layout* (door location, aisle orientation, length and width of aisles and number of aisles);
- *AS/RS configuration* (dimension of storage racks, number of cranes).

These layout problems affect warehouse performances in terms of:

- construction and maintenance costs;
- material handling costs;
- storage capacity;
- space utilization;
- equipment utilization.

Literature proposes several research works related to this issue. A number of papers discuss the pallet block-stacking problem.
Moder and Thornton (1965) focus on different ways of stacking pallets within a warehouse; Berry (1968) discusses the tradeoffs between storage efficiency and material handling costs through analytic models; Marsh (1979) uses simulation to evaluate the effect on space utilization of alternate lane depths and the rules for assigning incoming shipments to lanes; Marsh (1983) compares the layout design developed by using the simulation models developed in 1979 and the analytic models proposed by Berry (1968). Goetschalckx and Ratliff (1991) develop an efficient dynamic programming algorithm to maximize space utilization while Larson *et al.* (1997) propose an heuristic approach for the layout problem in order to maximize storage space utilization and minimize material handling cost.

Additional research works on the storage department layout are reported in: Roberts and Reed (1972), Bassan *et al.* (1980), Roll and Rosenblatt (1983), Pandit and Palekar (1993) and Roodbergen and Vis (2006).

Concerning the AS/RS configuration, some of the papers overviewed are the following: Karasawa *et al.* (1980) who present a nonlinear formulation with decision variables (i.e. the number of cranes, the height and length of storage racks, construction and equipment costs) under service and storage constraints. Ashayeri *et al.* (1985) solve a problem similar to Karasawa *et al.* (1980). Rosenblatt *et al.* (1993) propose a combined optimization and simulation approach derived from Ashayeri *et al.* (1985). Malmborg (2001) adopts simulation to evaluate some of the parameters then used in the closed form equations while Randhawa *et al.* (1991) and Randhawa and Shroff (1995) use simulation to investigate different I/O configurations on performance such as throughput, mean waiting time, and maximum waiting time.

The other topic of warehouse design and management is related to the *equipment selection* which has the objective to identify the automation level and storage and material handling systems to be employed in a warehouse.

There are a few research works in this field, see Cox (1986) and Sharp *et al.* (1994). Operation strategies have important effects on the overall system and can not be frequently changed. Such strategies concern the decision about different storage ways or decisions to use zone picking. The basic storage strategies include random storage, dedicated storage, class based storage, and Duration-of-Stay (DOS) based storage, as explained in Gu *et al.* (2007). Hausman *et al.* (1976), Graves *et al.* (1977) and Schwarz *et al.* (1978) make a comparison of random storage, dedicated storage, and class-based storage in single-command and dual-command AS/RS using both analytical models and simulations while Goetschalckx and Ratliff (1990) and Thonemann and Brandeau (1998) demonstrate theoretically that the DOS-based storage policies perform better in terms of traveling costs.

About zone picking approaches, some interesting research works are reported in Lin and Lu (1999), Bartholdi *et al.* (2000) and Petersen (2000).

1.5.6 The warehouse performance analysis

Performance evaluation approaches, i.e. benchmarking, analytical models and simulation, have the objective to provide information about the quality of a proposed design and/or operational policy in order to improve/to change it.

Warehouse benchmarking is the process of systematically assessing the performance of a warehouse, identifying inefficiencies, and proposing improvements (Gu *et al.*, 2007). A powerful tool for solving this problem is the Data Envelopment Analysis (*DEA*) which has the capability to capture simultaneously all the relevant inputs (resources) and outputs (performances), to identify the best performance domain and to delete the warehouse inefficiencies. Schefczyk (1993), Hackman *et al.* (2001) and Ross and Droge (2002) shows some approaches and case studies about using DEA in warehouse benchmarking.

Analytical models can be divided into:

- aisle based models which focus on a single storage system and address travel or service time, see Hwang and Lee (1990), Chang *et al.* (1995), Chang and Wen (1997), Lee (1997), Hwang *et al.* (2004b), Meller and Klote (2004), Roodbergen and Vis (2006);
- integrated models which address either multiple storage systems or criteria in addition to travel/service times, as reported in Malmborg (1996), Malmborg and Al-Tassan (2000).

1.5.7 Warehousing case studies and computational (or simulation) models

Some case studies on the applications of the various design and operation methods have been carried out, see Van Oudheusden *et al.* (1988), Zeng *et al.* (2002) and Dekker *et al.* (2004).

Successful research works on the implementation of warehouse computational or simulation models are rare. Perlmann and Bailey (1988) present a computer-aided design software that allows a warehouse designer to quickly generate a set of conceptual design alternatives including building shape, equipment selection, and operational policy selection, and to select from among them the best one based on the specified design requirements. Linn and Wysk (1990) develop an expert system for AS/ RS control. A similar AS/RS control system is proposed by Wang and Yih (1997) based on neural networks while Ito *et al.* (2002) propose an intelligent agent based system to model a warehouse, which is composed of three subsystems, i.e. agent-based communication system, agent-based material handling system, and agent-based inventory planning and control system. Macro and Salmi (2002) present a ProModel-based simulation tool of a warehouse used for analyzing the warehouse storage capacity and rack efficiency. Finally, Hsieh and Tsai (2006) implement a simulation model for finding the optimum design parameters of a real warehouse system.

1.6 Conclusions

This Chapter reports the results of the state of art overview on the Inventory and Warehouse Management carried out during the first part of the PhD course. More in detail, the state of art analysis on Inventory Management highlights that:

- the classical inventory control policies don't include stochastic variables;
- literature reports inventory management policies which don't consider inventory constraints due to demand intensity, demand variability and lead times;
- simulation model implemented are ad-hoc built simulation models because they reproduce a specific manufacturing system or supply chain.

Moreover, from the state of art analysis on the Warehouse Management becomes clear that research studies on warehouse management simulation are rare and they aim at solving particular problems under constraints (i.e. material flow, size and dimension of the warehouse, warehouse equipment selection, etc).

References

Al-Rifai, M.H., Rossetti, M.D., 2007. An efficient heuristic optimization algorithm for a two-echelon (R, Q) inventory system. *Production Economics*, 109, 195-213.

Ashayeri, J., Gelders, L., Wassenhove, L.V., 1985. A microcomputer-based optimization model for the design of automated warehouses. *Production Research*, 23 (4), 825-839.

Azadivar, F., 1989. Optimum allocation of resources between the random access and rack storage spaces in an automated warehousing system. *Production Research*, 27 (1), 119-131.

Bartholdi, J.J., Eisenstein, D.D., Foley, R.D., 2000. Performance of bucket brigades when work is stochastic. *Operations Research*, 49 (5), 710-719.

Bassan, Y., Roll, Y., Rosenblatt, M.J., 1980. Internal layout design of a warehouse. *AIIE Transactions*, 12 (4), 317-322.

Bassin, W.M., 1990. A Technique for Applying EOQ Models to Retail Cycle Stock Inventories. *Small Business Management*, 28 (1), 48-55.

Bhaskaran, S., 1998. Simulation analysis of a manufacturing supply chain. *Decision Sciences*, 29 (3), 633-657.

Berry, J.R., 1968. Elements of warehouse layout. *Production Research*, 7 (2), 105-121.

Bertazzi, L., Paletta, G., Speranza, M.G., 2005. Minimizing the total cost in an integrated vendor-managed inventory system. *Journal of Euristics*, 11, 393-419.

Briggs, J.A., 1978. Warehouse operations planning and management. Krieger Publishing Company, New York.

Chang, D.T., Wen, U.P., Lin, J.T., 1995. The impact of acceleration/deceleration on travel-time models for automated storage/retrieval systems. *IIE Transactions*, 27, 108-111.

Chang, D.T., Wen, U.P., 1997. The impact of rack configuration on the speed profile of the storage and retrieval machine. *IIE Transactions*, 29, 525-531.

Chen, F. and Krass, D., 2001. Inventory models with minimal service level constraints. *Operational Research*, 134, 120-140.

Chen, C., Lee, W., 2004. Multi-objective optimization of multi-echelon supply chain networks with uncertain product demands and prices. *Computers and Chemical Engineering*, 28, 1131-1144.

Coyle, J., Bardi, E., Langley, C., 2003. The management of business Logistic: a supply chain perspective. Mason.

Cormier, G., 2005. Operational research methods for efficient warehousing. In: Langevin, A., Riopel, D. (Eds.), Logistics Systems: Design and Optimization. Springer, Berlin, 93-122.

Cormier, G., Gunn, E.A., 1992. A review of warehouse models. *Operational Research*, 58, 3-13.

Cormier, G., Gunn, E.A., 1996. On coordinating warehouse sizing, leasing and inventory policy. *IIE Transactions*, 28, 149-154.

Cormier, G., Gunn, E.A., 1996. Simple models and insights for warehouse sizing. *Operational Research*, 47, 690-696.

Cox, B., 1986. Determining economic levels of automation by using a hierarchy of productivity ratios techniques. *Proceedings of 7th International Conference on Automation in Warehousing*.

Dellaert, N., De Kok, T., 2004. Integrating resource and production decisions in a simple multi-stage assembly system. *Production Economics*, 90, 281-294.

Dekker, R., de Koster, M.B.M., Roodbergen, K.J., van Kalleveen, H., 2004. Improving order-picking response time at Ankor's warehouse. *Interfaces*, 34 (4), 303-313.

D'Esopo, A., 1968. An ordering policy for stock items when delivery can be expedited. *Operations Research*, 16 (4), 880-883.

De Sensi, G., Longo, F., Mirabelli, G., 2008. Inventory policies analysis under demand patterns and lead times constraints in a real supply chain. *Production Research*, 46, 6997-7016.

Eben-Chaime, M., Pliskin, N., 1997. Operations Management of multiple machine automatic warehousing systems. *Production Economics*, 51, 83-98.

Francis, R.L., 1967. On some problems of rectangular warehouse design and layout. *Industrial Engineering*, 18, 595-604.

Fuerst, W.L., 1981. Small Business Get A New Look at ABC Analysis for Inventory Control. *Small Business Management*, 19 (3), 39-44.

Ganeshan, R., 1999. Managing supply chain inventories: a multiple retailer, one warehouse, multiple supplier model. *Production Economics*, 59, 341-354.

Giannoccaro, I., Pontrandolfo, P., 2002. Inventory management in supply chains: a reinforcement learning approach. *Production Economics*, 78, 153-161.

Goetschalckx, M., Ratliff, H.D., 1990. Shared storage policies based on the duration stay of unit loads. *Management Science*, 36 (9), 1120-1132.

Goetschalckx, M., Ratliff, H.D., 1991. Optimal lane depths for single and multiple products in block stacking storage systems. *IIE Transactions*, 23 (3), 245-258.

Goh, M., Ou, J., Teo, C.P., 2001. Warehouse sizing to minimize inventory and storage costs. *Naval Research Logistics*, 48 (4), 299-312.

Goldsby, T., Martichenko, R., 2005. Lean Six Sigma Logistics: Strategic Development to Operational Success. Boca Raton: J. Ross Publishing.

Graves, S.C., Hausman, W.H., Schwarz, L.B., 1977. Storage-retrieval interleaving in automatic warehousing systems. *Management Science*, 23 (9), 935-945.

Gray, A.E., Karmarkar, U.S., Seidmann, A., 1992. Design and operation of an order consolidation warehouse: models and applications. *Operational Research*, 58, 14-36.

Gu, J.X., Goetschalckx, M., McGinnis, L.F., 2007. Research on warehouse operation: A comprehensive review. *Operational Research*, 177 (1), 1-21.

Hackman, S.T., Frazelle, E.H., Griffin, P.M., Griffin, S.O., Vlasta, D.A., 2001. Benchmarking warehouse and distribution operations: An input–output approach. *Productivity Analysis*, 16, 79-100.

Hausman, W.H., Schwarz, L.B., Graves, S.C., 1976. Optimal storage assignment in automatic warehousing systems. *Management Science*, 22 (6), 629–638.

Heragu, S.S., Du, L., Mantel, R.J., Schuur, P.C., 2005. Mathematical model for warehouse design and product allocation. *Production Research*, 43 (2), 327-338.

Hsieh, L.F., Tsai, L., 2006. The optimum design of a warehouse system on order picking efficiency. *Advanced Manufacturing Technology*, 28, 626-637.

Huang, H.C., Chew, E.P., Goh, K.H., 2005. A two-echelon inventory system with transportation capacity constraint. *Operational Research*, 167, 129-143.

Hung, M.S., Fisk, C.J., 1984. Economic sizing of warehouses – A linear programming approach. *Computers and Operations Research*, 11 (1), 13-18.

Hwang, H., Lee, S.B., 1990. Travel-time models considering the operating characteristics of the storage and retrieval machine. *Production Research*, 28 (10), 1779-1789.

Hwang, H., Song, Y.-K., Kim, K.-H., 2004b. The impacts of acceleration/deceleration on travel time models for carousel systems. *Computers and Industrial Engineering*, 46, 253-265.

Inderfurth, K., Minner, S., 1998. Safety stocks in multi-stage inventory systems under different service measures. *Operational Research*, 106, 57-73.

Ito, T., Abadi, J., Mousavi, S.M., 2002. Agent-based material handling and inventory planning in warehouse. *Intelligent Manufacturing*, 13 (3), 201-210.

Karasawa, Y., Nakayama, H., Dohi, S., 1980. Trade-off analysis for optimal design of automated warehouses. *Systems Science*, 11 (5), 567-576.

Korpela, J., Tuominen, M., 1996. A decision aid in warehouse site selection. *Production Economics*, 45, 169-180.

Larson, N., March, H., Kusiak, A., 1997. A heuristic approach to warehouse layout with class-based storage. *IIE Transactions*, 29, 337-348.

Lee, H., Billington, C., 1993.Material management in decentralized supply chains. *Operations Research*, 41 (5), 835-847.

Lee, H.S., 1997. Performance analysis for automated storage and retrieval systems. *IIE Transactions*, 29, 15-28.

Lee, H.T., Wu, J.C., 2006.A study on inventory replenishment policies in a two-echelon supply chain system. *Computers and Industrial Engineering*, 51, 257-263.

Levy, J., 1974. The optimal size of a storage facility. *Naval Research Logistics Quarterly*, 21 (2), 319-326.

Lin, E., 1980. Inventory Control System for Small Business. *American Journal of Small Business*, 4 (4), 11-19.

Lin, C.H., Lu, I.Y., 1999. The procedure of determining the order picking strategies in distribution center. *Production Economics*, 301-307.

Linn, R.J., Wysk, R.A., 1990. An expert system framework for automated storage and retrieval system control. *Computers and Industrial Engineering*, 18 (1), 37-48.

Longo, F., Ören, T., 2008. Supply chain vulnerability and resilience: a state of the art overview. *Proceedings of the 20th European Modeling and Simulation Symposium*, 17-19 September, Campora S.Giovanni, Cosenza (Italy), 527-533.

Longo, F., Mirabelli, G., 2008. An advanced supply chain management tool based on modeling and simulation. *Computer and Industrial Engineering*, 54 (3), 570-588.

Lowe, T.J., Francis, R.L., Reinhardt, E.W., 1979. A greedy network flow algorithm for a warehouse leasing problem. *AIIE Transactions*, 11 (3), 170-182.

Macro, J.G., Salmi, R.E., 2002. A simulation tool to determine warehouse efficiencies and storage allocations. *Proceedings of the 2002 Winter Simulation Conference*, 08-11 December, San Diego, California (USA), 1274-1281.

Malmborg, C.J., 1996. An integrated storage system evaluation model. *Applied Mathematical Modelling*, 20 (5), 359-370.

Malmborg, C.J., Al-Tassan, K., 2000. An integrated performance model for order picking systems with randomized storage. *Applied Mathematical Modelling*, 24 (2), 95-111.

Malmborg, C.J., 2001. Rule of thumb heuristics for configuring storage racks in automated storage and retrieval systems design. *Production Research*, 39 (3), 511-527.

Marsh, W.H., 1979. Elements of block storage design. *Production Research*, 17 (4), 377-394.

Marsh, W.H., 1983. A comparison with Berry. *Production Research*, 21 (2), 163-172.

Mason, S.J., Ribera, P.M., Farris, J.A., Kirk, R.G., 2003. Integrating the warehousing and transportation functions of the supply chain. *Transportation Research E*, 39, 141-159.

Meller, R.D., Gau, K.Y., 1996. The facility layout problem: Recent and emerging trends and prospectives. *Manufacturing Systems*, 15 (5), 351-366.

Meller, R.D., Klote, J.F., 2004. A throughput model for carousel/VLM pods. *IIE Transactions*, 36 (8), 725-741.

Minner, S., Diks, E.B., De Kok, A.G., 1999. A two-echelon inventory system with supply lead time flexibility. *IIE Transactions*, 35, 117-129.

Minner, S., 2000. Strategic Safety Stocks in Supply Chains. Lecture Notes in Economics and Mathematical Systems. Springer, Berlin.

Minner, S., 2003. Multiple-supplier inventory models in supply chain management: a review. *Production Economics*, 81, 265-279.

Moder, J.J., Thornton, H.M., 1965. Quantitative analysis of the factors affecting floor space utilization of palletized storage. *Industrial Engineering*, 16 (1), 8-18.

Moinzadeh, K., Nahmias, S., 1988. A continuous review model for an inventory system with two supply modes. *Management Science*, 34, 761-773.

Moinzadeh, K., Schmidt, C.P., 1991. An (S_1, S) inventory system with emergency orders. *Operations Research*, 39, 308-321.

Moinzadeh, K., Aggarwal, P.K., 1997. An information based multiechelon inventory system with emergency orders. *Operations Research*, 45, 694-701.

Mulcahy, E.D., 1994. Warehouse distribution and operation handbook. McGraw-Hill, USA.

Onwubolu, G.C., Dube, B.C., 2006. Implementing an Improved Inventory Control System in a Small Company: A Case Study. *Production Planning & Control*, 17 (1), 67-76.

Pandit, R., Palekar, U.S., 1993. Response time considerations for optimal warehouse layout design. *Engineering for Industry*, 115, 322-328.

Park, Y.H., Webster, D.B., 1989. Modelling of three-dimensional warehouse systems. *Production Research*, 27 (6), 985-1003.

Perlmann, A.M., Bailey, M., 1988. Warehouse logistics systems – A CAD model. *Engineering Costs and Production Economics*, 13, 229-237.

Petersen, C.G., 2000. An evaluation of order picking policies for mail order companies. *Production and Operations Management*, 9 (4), 319-335.

Pliskin, J.S., Dori, D., 1982. Ranking alternative warehouse area assignments: A multiattribute approach. *IIE Transactions*, 14 (1), 19-26.

Qi, X., Bard, J., Yu, G., 2004. Supply chain coordination with demand disruptions. *Omega*, 32, 301-312.

Rajuldevi, M.K., Veeramachaneni, R., Kare, S., 2009. Warehousing in theory and practice. Boras School of Engineering, Sweden.

Ramasesh, R., Keith, O., Hayya, J., 1991. Sole versus dual sourcing in stochastic lead-time (s, Q) inventory model. *Management Science*, 37, 4, 428-443.

Randhawa, S.U., McDowell, E.D., Wang, W.-T., 1991. Evaluation of scheduling rules for single- and dual-dock automated storage/retrieval system. *Computers and Industrial Engineering*, 20 (4), 401-410.

Randhawa, S.U., Shroff, R., 1995. Simulation-based design evaluation of unit load automated storage/retrieval systems. *Computers and Industrial Engineering*, 28 (1), 71-79.

Rao, A.K., Rao, M.R., 1998. Solution procedures for sizing of warehouses. *Operational Research*,108, 16-25.

Roberts, S.D., Reed, R., 1972. Optimal warehouse bay configurations. *AIIE Transactions*, 4 (3), 178-185.

Roll, Y., Rosenblatt, M.J., 1983. Random versus grouped storage policies and their effect on warehouse capacity. *Material Flow*, 1, 199-205.

Roodbergen, K.J., Vis, I.F.A., 2006. A model for warehouse layout. *IIE Transactions*, 38 (10), 799-811.

Rosenblatt, M.J., Roll, Y., 1984. Warehouse design with storage policy considerations. *Production Research*, 22 (5), 809-821.

Rosenblatt, M.J., Roll, Y., 1988. Warehouse capacity in a stochastic environment. *Production Research*, 26 (12), 1847-1851.

Rosenblatt, M.J., Roll, Y., Zyser, V., 1993. A combined optimization and simulation approach for designing automated storage/retrieval systems. *IIE Transactions*, 25 (1), 40-50.

Ross, A., Droge, C., 2002. An integrated benchmarking approach to distribution center performance using DEA modeling. *Operations Management*, 20, 19-32.

Rowenhorst, B., Reuter, B., Stockrahm, V., Van Houtum, G.J., Mantel, R.J., Zijm, W.H.M., 2000. Warehouse design and control: Framework and literature review. *Operational Research*, 122, 515-533.

Scarf, H., 1960. The optimality of (s, S) policies in the dynamic inventory problem. Mathematical Methods in the Social Sciences. Stanford University Press, Stanford, California.

Schefczyk, M., 1993. Industrial benchmarking: A case study of performance analysis techniques. *Production Economics*, 32, 1-11.

Schwarz, L.B., Graves, S.C., Hausman, W.H., 1978. Scheduling policies for automatic warehousing systems: Simulation results. *AIIE Transactions*, 10 (3), 260-270.

Sharp, G.P., Vlasta, D.A., Houmas, C.G., 1994. Economics of storage/retrieval systems for item picking. Material Handling Research Center, Georgia Institute of Technology, Atlanta, Georgia.

Silver, E.A., Pyke, D.F., Peterson, R., 1998. Inventory Management and Production Planning and Scheduling. John Wiley & Sons, USA.

Simchi-Levi, D., Kaminsky, P., Simchi-Levi, E., 2007. Managing the Supply Chain: the definitive guide for the business professional. McGraw-Hill College.

Thonemann, U.W., Brandeau, M.L., 1998. Optimal storage assignment policies for automated storage and retrieval systems with stochastic demands. *Management Science*, 44 (1), 142-148.

Toomey, J.W., 2000. Inventory Management: Principles, Concepts and Techniques. Norwell: Kluwer Academic Publishers.

Tompkins, A., Smith, D., Jerry, D., 1998. The warehouse management handbook. Tompkins Press.

Van den Berg, J.P., 1999. A literature survey on planning and control of warehousing systems. *IIE Transactions*, 31, 751-762.

Van Oudheusden, D.L., Tzen, Y.J., Ko, H.T., 1988. Improving storage and order picking in a person-on-board AS/R system: a case study. *Engineering Costs and Production Economics*, 13, 273-283.

Wang, J.Y., Yih, Y., 1997. Using neural networks to select a control strategy for automated storage and retrieval systems (AS/RS). *Computer Integrated Manufacturing*, 10 (6), 487-495.

White, J.A., Francis, R.L., 1971. Normative models for some warehouse sizing problems. *AIIE Transactions*, 9 (3), 185-190.

Yoon, C.S., Sharp, G.P., 1996. A structured procedure for analysis and design of order pick systems. *IIE Transactions*, 28, 379-389.

Zeng, A.Z., Mahan, M., Fluet, N., 2002. Designing an efficient warehouse layout to facilitate the order-filling process: An industrial distributor's experience. *Production and Inventory Management Journal*, 43 (3-4), 83-88.

Zhou, B., Zhao, Y., Katehakis, M., 2007. Effective control policies for stochastic inventory systems with a minimum order quantity and linear costs. *Production Economics*, 106, 523-531.

CHAPTER 2

Modeling & Simulation in Production and Logistic systems

2.1 Introduction

During the last years several research works in the area of Modeling and Simulation (*M&S*) applied to production and logistic systems have been proposed (Callahan *et al.*, 2006). The M&S approach generally does not provide exact or optimal solutions to problems but allows the users to analyze the behavior of complex system, to perform what-if analysis and choose correctly various scenarios (Karacal, 1998; Banks, 1998). In fact, oppositely to analytical approaches, the main advantage of M&S when studying and analyzing manufacturing and logistic systems is the possibility to take into consideration multiple aspects without introducing restrictive assumptions.

Other advantages of M&S include (Banks, 1998):

- understanding why certain phenomena occur in real systems;
- diagnosing problems considering all the interactions which take place in a given moment;
- identifying constraints, e.g. performing bottleneck analysis, it is possible to discover the causes of delays;
- building consensus by presenting design changes and their impact on the real system;
- specifying requirements during the system design.

A state of art overview highlights a great number of research works in the field of M&S for production and logistic systems. Many of them concern with manufacturing systems M&S (Berry, 1972; Nunnikhoven and Emmons, 1977; Stenger, 1996; Mullarkey *et al.*, 2000; Heidi *et al.*, 2001; Longo *et al.*, 2005). Many others focus on supply chain M&S (Thomas and Griffin, 1996; Forza, 1996; Erenguk and Vakharia, 1999).

As before mentioned, according to Banks (1998), simulation plays an important role above all for its main property to provide what-if analysis and to evaluate all the benefits and issues related to the environment where it is applied.

Conducting a successful simulation study is a difficult task: a large experience is required in the modeling phase, in the input data analysis as well as in designing correctly simulation experiments and analyzing simulation results. Therefore, the first part of the PhD course has been devoted to the acquisition of the main M&S principles by developing two application examples (a manufacturing system simulation model and a supply chain simulation model). This part of the PhD course (to be regarded as a training part) has been carried out jointly with the state of the art analysis in the area of inventory and warehouse management presented in Chapter 1.

Before getting into details of the application examples, in the sequel a brief overview of Chapter 2 is reported. Section 2.2 presents a simulation model of a real manufacturing system (in addition, a description of the main steps of the simulation study is reported). Section 2.3 proposes a supply chain simulation model integrated with artificial intelligence techniques. Finally, conclusions are presented in Section 2.4. Note that these application examples have been implemented to correctly acquire the main Modeling & Simulation principles and the statistical methodologies needed for carrying out a successful simulation study.

2.2 The First Application Example: a simulation model of a real manufacturing system

The manufacturing system being analyzed in this application example produces high pressures hydraulic hoses and it is located in Calabria (southern Italy). The industrial plant belongs to a multinational company specialized in design, production and distribution of rubber hoses. The *L-shape* plant layout (see Figure 2.1) covers a surface of 13000 m^2 and is subdivided into three operative sectors:

- the mechanic sector;
- the assembly sector;
- the warehouse.

The mechanic sector manufactures ring nuts and junctions; it covers two different areas. The first one cuts metallic sheets and the second one, starting from the items coming from the previous working area, manufactures ring nuts and junctions.

In the assembly area, ring nuts, junctions, lock-washers and hydraulic hoses are assembled.

The warehouse is also subdivided into two areas: in the first one, the biggest, there are raw materials and in the second one, final products (assembled hydraulic hoses).

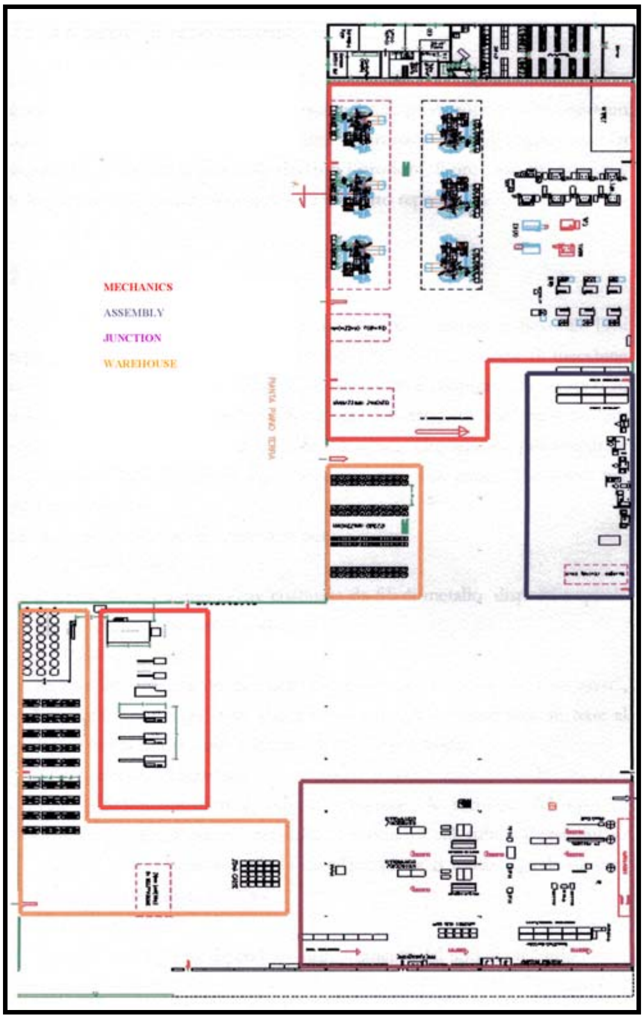


Figure 2.1 – The *L-shape* plant layout

2.2.1 The Simulation Model of the manufacturing system

After different meetings with the company top management, we decided to implement a simulation model by using the commercial package eM-Plant™ by *Tecnomatix Technologies* (a discrete event-oriented simulation tool) aiming at studying different scenarios (in terms of resources availability) for one of the most important department of the manufacturing system.

During the implementation phase, two objectives are pursued:

- the development of a simulation model to be used for carrying out what-if analysis (investigating different operative scenarios) and improving system performance;
- the development of a simulation model to be successively used for shop orders scheduling and inventory management.

The initial steps of the simulation study, problem formulation and setting of objectives (Banks, 1998), have highlighted two critical issues (for the modeling phase):

- the simulation model flexibility (a model architecture capable of easily integrating future changes, in other words, the capability of recreating an evolving real system);
- the time for executing simulation runs (if the simulator has to be used for real time supporting the manufacturing process management, a time-efficient simulator is needed).

To this end, an advanced modeling approach different from the classical one is adopted. In fact, the classical approach is based on library objects that can be used for reproducing static and dynamic entities: Figure 2.2 shows the material flow library provided by the software for modeling machines, workstations, conveyors, queues, transporters, etc.

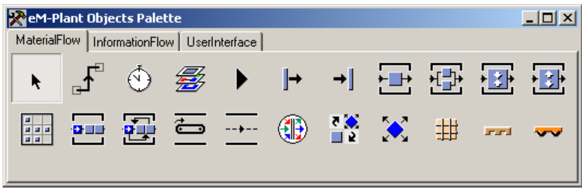


Figure 2.2 – The Material Flow Library

Such approach could give some problems in recreating the real system: sometimes the objects provided by the software libraries are not capable of recreating the real system with satisfactory accuracy. In addition, the high number of dynamic entities flowing in the simulation model (consider that the real plant manufactures, on the average, 1000 hydraulic hoses per day) could terribly increase the time required for executing a simulation run. In effect, consider that each entity defined in the simulation model is a class that requires memory until leaving the system (*entity destruction*); in other words the higher is the number of entities flowing in the simulation model, the higher is the memory required and the CPU utilization level and the higher is the time needed for executing a simulation run.

The advanced approach introduced substitutes the flow of entities with a flow of information stored in tables and uses ad-hoc programmed routines for implementing all the logics and rules governing the system (by using programming code to recreate the real system it becomes easy the implementation of future changes). To this end, particular attention has been paid in creating model documentation and commenting the programming code.

Usually dynamic entities flowing in a discrete event simulation model determine the events list evolution. In this modeling approach the information flow replaces the entities flow and the library object “event generator” takes care of the events list management.

Note that each dynamic entity is a class instanced in the model, so, by deleting such classes and their computational load, a "light" simulator is obtained.

For a better understanding of the proposed approach, consider, for instance, the simulation model initialization: it consists in filling up the system with raw materials, components, shop orders in correspondence of each machine, etc. In the classical approach each shop order is an entity flowing in the model whereas in our approach each shop order is a row of a table in which are reported all the information necessary for its complete description. The events list management is assured by event generator objects. Consider, for instance, the following events: "beginning of the shift at the cutting machine" and "beginning of the cutting operations related to a specific shop order". In the first case an event generator takes care of generating the event "beginning of the shift". In the second case the event management is more complex: a process time in a manufacturing system is usually a stochastic time so at the "beginning of the cutting operation" the event of "cutting operation end" have to be defined. In this case, by means of programming code and in correspondence of the "beginning" event, the event generator object creates an event to be executed when the stochastic process time is elapsed. Another method (*programming code*) could be used for recording in a table all the information about the shop order processed at the cutting machine, i.e. shop order arrival time, shop order process time, etc.

This example allows to understand how the programming code works and how programming code, event generators and tables interact for recreating the real system evolution.

The only disadvantage of this approach is related to simulation model animation. Even if in a discrete event simulation model the animation which is strictly related to entities flow, usually has a key-role, in this case animation is not considered a priority aspect of the simulation study (however, the architecture of the model is ready for implementing the animation).

Such approach increases model flexibility and allows to achieve great advantages in terms of time required for executing a simulation run.

2.2.2 The Simulation Model implementation

The simulator main frame is called *model* and it contains 12 secondary frames. Each frame reproduces a specific process of the real system (assembly departments). The frames are named as follows:

- *Prod_Manager*: it generates the production planning;
- *Preparation*: it recreates the raw materials preparation;
- *Fittings stamp*: it recreates the fittings stamp operations;

- *Cut*: it recreates the cutting operations;
- *Skinning operation*: it recreates the hose skinning operations;
- *Assembly*: it recreates the assembly operations;
- *Junction*: it recreates the junction operations;
- *Testing operation*: it recreates the hoses testing operations;
- *Packaging*: it recreates the final controls and packaging operations;
- *Performance*: it evaluates performance indexes values;
- *Dialog*: it implements the GUI (*Graphic User Interface*).

Now each secondary frame is described in detail.

The *Prod_Manager* implements all the rules and logics for production planning. In particular, this object recreates customers' orders inserting, the inventory management, the raw material allocation and the short period production planning. Its function is similar to the production planning office of the real system. Shop Orders (here in after *SOs*), generated at the beginning of the simulation and during the simulation by means of specific routines, are stored in tables. Note that in the classical modeling approach each SO is a dynamic entity (characterized by specific attributes) flowing in the model; in the advanced approach each SO corresponds to a specific row of a table and the cell values corresponds to the entity attributes. The information flow is guaranteed by the "event generator" objects.

Figure 2.3 shows the *Prod_Manager* architecture, note that there are only three different type of library objects: Tables for storing information (see the first object in the top-left corner), Methods for programming code (see the M-shape icons) and Event Generators for event lists management (see the second object in the top-left corner).

In the *Prod_Manager* four different sections can be distinguished:

- the *customers' orders inserting*;
- the *inventory management*;
- the *material allocation*;
- the *production planning*.

In the *customers' orders inserting*, each customers' order (SO) is inserted in the production planning according to its due date; if the due date is greater than 45 days, the SO is inserted at the end of the SOs queue otherwise it is inserted in some positions with due date lower than 45 days. This distinction is adopted to implement SOs generation in the simulation model.

Figure 2.4 shows the block diagram of the customers' orders inserting process.

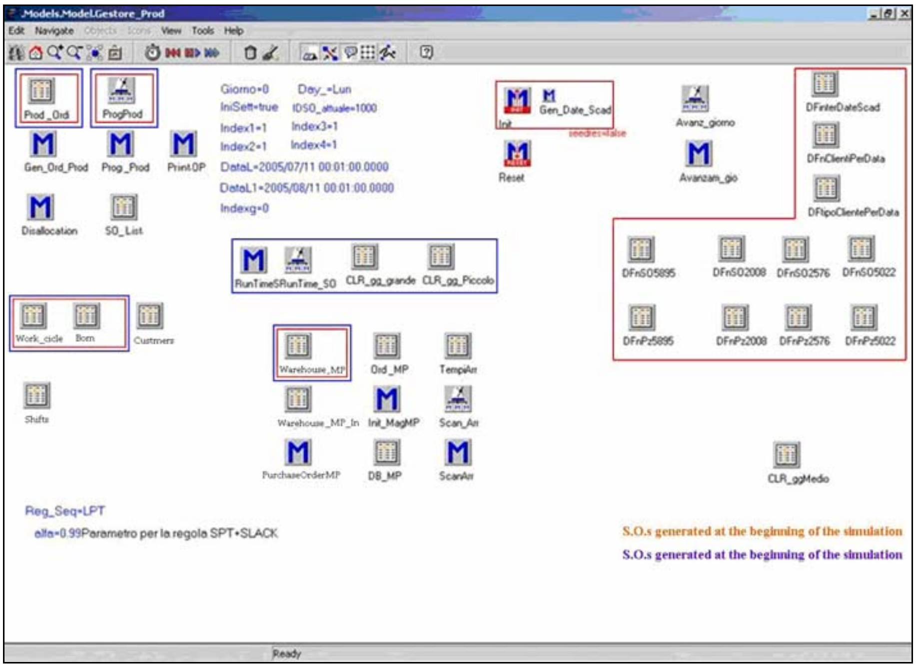


Figure 2.3 – The Modeling Frame for Production Planning

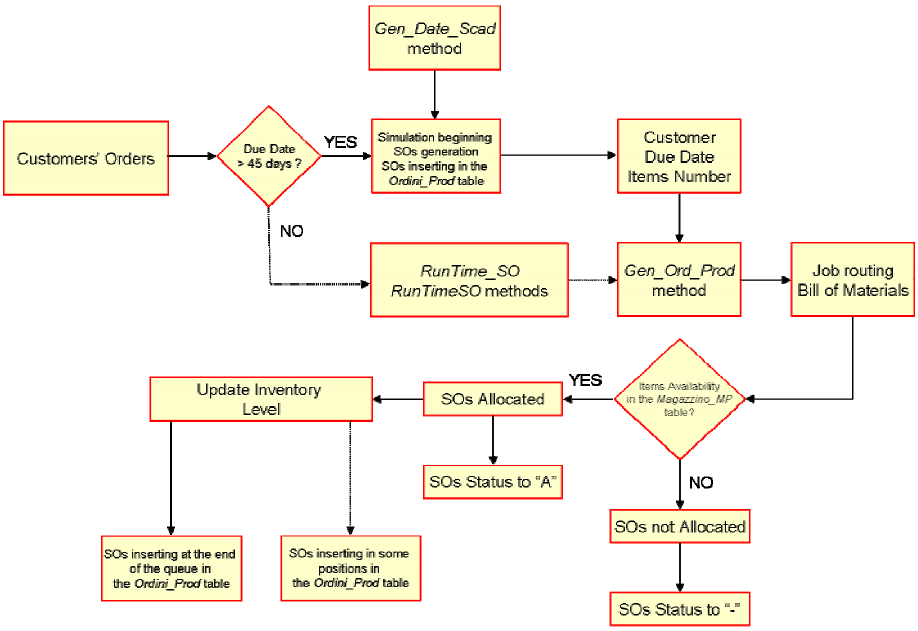


Figure 2.4 – The Customers' Orders Inserting Process

At the beginning of the simulation, the generated SOs are inserted in the *Prod_Orders* table. By calling the routine *Gen_Date_Scad*, all the information related to customers, due date and items number for each SO are obtained. In the second step, the *Gen_Ord_Prod* routine is called in order to evaluate the product family for each SO with the job routing and the bill of material. Before inserting each SO in the *Prod_Orders* table, the same method makes a check on the raw material availability by accessing the *Warehouse_MP* table.

As reported in the block diagram, if the inventory level is enough, the SO is allocated with the status "A" and inserted at the end of the *Prod_Orders* table otherwise the SO is not allocated and its status is changed to "- ". SOs with due date lower than 45 days are generated during the simulation by the *RunTime_SO* and *RunTimeSO* routines while the procedure for inserting them in the *Prod_Orders* table is the same of orders generated at the beginning of simulation.

The *inventory management* section is related to orders emission, material deliveries and warehouse initialization. In detail, the block diagram reported in Figure 2.5 shows the order emission procedure. At the beginning of each day, the method *Prog_Prod* is called to verify if in the *Prod_Orders* table there are SOs in the "not allocated" status. If there is a SO not allocated, the *PurchaseOrderMP* routine starts to work for evaluating the quantity to be ordered (from the *DB_MP* table) and for defining the arriving date for each order (according to suppliers' lead times). All these information are stored in the *ArrTimes* table.

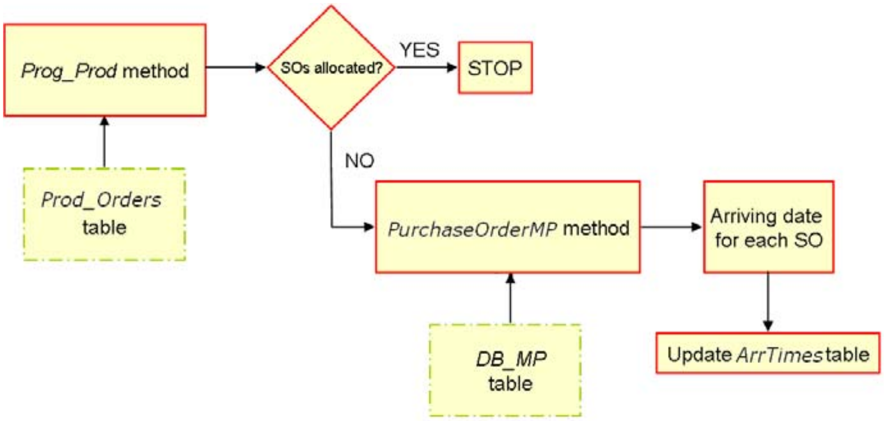


Figure 2.5 – The Inventory Management Process

The *material allocation* section deals with material allocation in function of SOs with closer due date. The method *Prog_Prod* chooses (from Prod_Orders table) the SOs not allocated and calls the *Disallocation* method which allocates materials to the SO considered taking them from SOs with greater due date, see Figure 2.6.

The *production planning* section implements all the rules for a correct orders scheduling.

At the beginning of the day, the *Prog_Prod* event generator calls the *Prog_Prod* method; at the beginning of the week, this method in the *Prod_Orders* table considers all the SOs allocated and uploads them in the *Printed_SO* table. These SOs are ready to start the working cycle. The block diagram of the production planning process is reported in Figure 2.7.

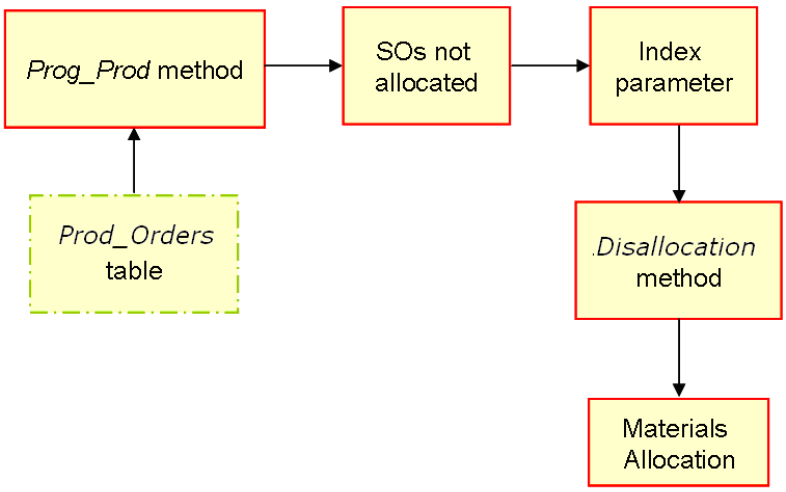


Figure 2.6 – The Material Allocation

The *Preparation* modeling frame implements all the rules related to the first operation of the job routing, the raw material preparation. The worker takes the raw material SOs from warehouse shelves and sorts them according to the scheduling rules suggested by the production planning office. As in the previous case only three types of library objects forms the frame architecture opportunely subdivided in three sections: the first section for collecting and scheduling SOs; the second for defining the specific manufacturing operations associated to each SO; the third for collecting performance indexes values during the simulation.

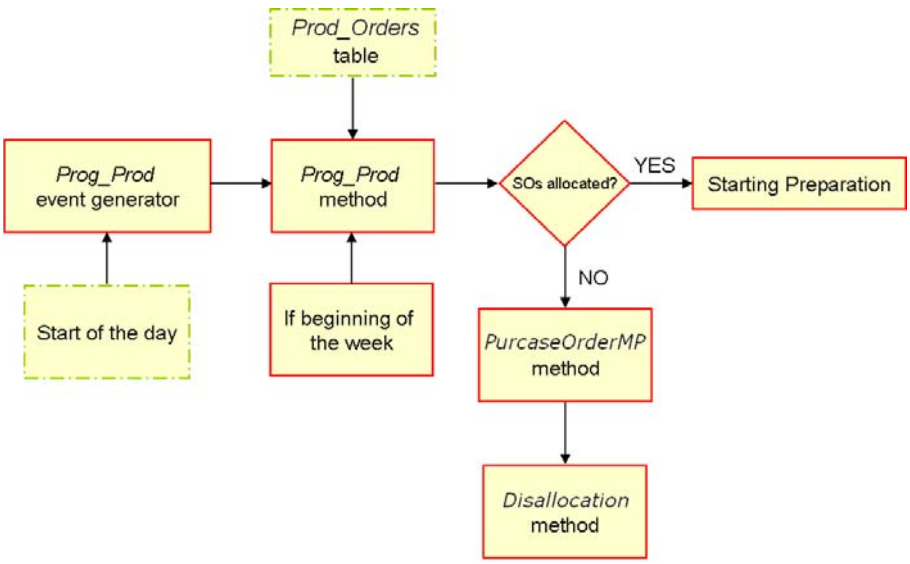


Figure 2.7 – The Production Planning

The remaining frames have the same architecture of the previous one. Only the *Cut* modeling frame (that recreates cutting operations, see Figure 2.8) implements specific features. In the actual configuration workers manually execute cutting operations. As required by the company top management the simulator should also be used for evaluating system performance under different cutting scenarios. To this end, in addition to the manual operation, an automated cutting process has been implemented. The results of such analysis will be discussed later on.

Note that in order to guarantee a high flexibility level in terms of future changes implementation each manufacturing system department has been modeled by adopting the same modeling architecture.

The *Performance* modeling frame collects during the simulation the daily values of the performance indexes chosen, i.e. the average flow time, the average lateness, the average tardiness, the departments utilization degrees, the departments production.

Note that these performance indexes have been selected both to use the simulator for analyzing different operative scenarios (as in the case of the cutting departments) and for supporting the manufacturing process management, e.g. SOs scheduling.

Finally the *Dialog* frame implements the graphic user interface (*GUI*) for setting system parameters before starting the simulation, e.g. SOs scheduling rules, simulation length, etc.

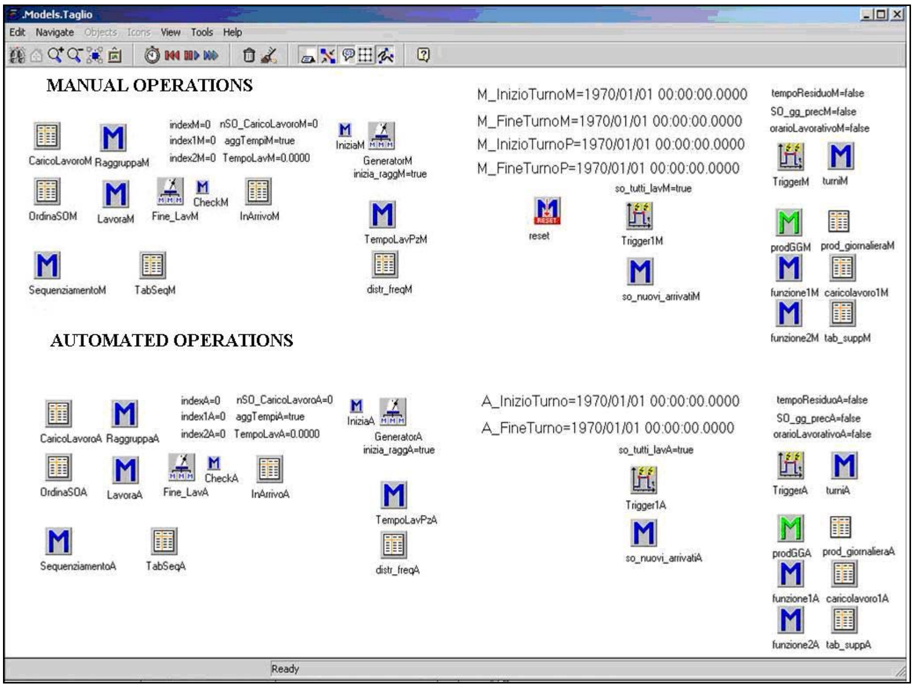


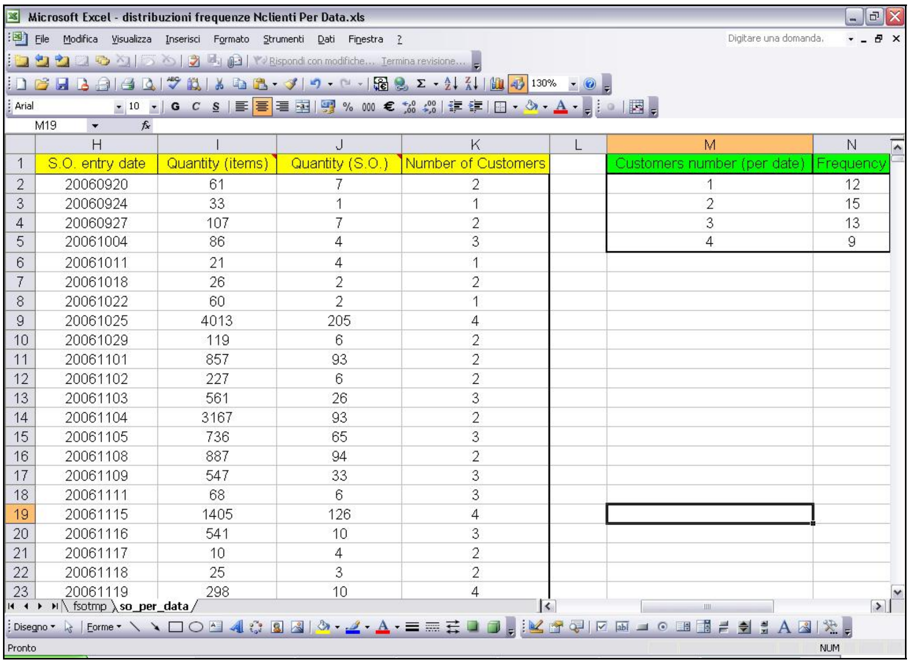
Figure 2.8 – The Modeling frame for Cutting operations

2.2.3 The Input data analysis

The simulator is directly connected with the company informative system by means of MS Excel spreadsheets. The company informative system makes these spreadsheets updated with historical data of the last six months, such as:

- products;
- customers;
- process times;
- stocks and refurbishment times;
- due dates;
- frequency of customers requiring orders;
- frequency of customers' orders;
- number of SOs for each customer;
- quantity for each SO.

The MS Excel spreadsheets have been organized for calculating empirical distribution starting from input data. In fact, the simulator receives as input the empirical distributions: see Figure 2.9 for the empirical distribution of customers' number per date.



	S.O. entry date	Quantity (items)	Quantity (S.O.)	Number of Customers		Customers number (per date)	Frequency
2	20060920	61	7	2		1	12
3	20060924	33	1	1		2	15
4	20060927	107	7	2		3	13
5	20061004	86	4	3		4	9
6	20061011	21	4	1			
7	20061018	26	2	2			
8	20061022	60	2	1			
9	20061025	4013	205	4			
10	20061029	119	6	2			
11	20061101	857	93	2			
12	20061102	227	6	2			
13	20061103	561	26	3			
14	20061104	3167	93	2			
15	20061105	736	65	3			
16	20061108	887	94	2			
17	20061109	547	33	3			
18	20061111	68	6	3			
19	20061115	1405	126	4			
20	20061116	541	10	3			
21	20061117	10	4	2			
22	20061118	25	3	2			
23	20061119	298	10	4			

Figure 2.9 – Customers' number per date, empirical distribution

2.2.4 The simulation model Verification and Validation

According to Banks (1998), verification is the process of determining that a model implementation accurately reflects developer conceptual description and specifications. In this specific case, the simulation model verification has been made using the *debugging technique* which consists in debugging the model, following an iterative procedure, in order to find and delete all the bugs due to model translation.

From the other side, validation aims at quantifying the degree to which a model is an accurate representation of the real world from the perspective of the intended use of the model (Banks, 1998). Production data in the period from January 2006 to December 2006 are used for validating the simulation model. The validation process is made up by two different steps:

- evaluation of the simulation run length;
- validation using the *Face Validation* technique.

The simulation run length evaluation is generally the starting point of the validation process. A simulation run must be long enough to guarantee reliable statistic results; in fact, a longer simulation run does not give additional information and requires more time to be executed.

The approach adopted for defining the correct simulation run length is the Mean Square Pure Error analysis (*MS$_{PE}$*) considering as performance index the plant mean daily production. As reported in Figure 2.10, after 160 days the value of the MS$_{PE}$ of the mean daily production is small enough for assuring the goodness of the simulation model statistic results. The value of the Mean Square pure Error has been used for calculating a confidence interval and such confidence interval has been compared with the confidence interval obtained by real data. The confidence intervals are quite similar so it is possible to conclude that 160 days is the optimal simulation run length.

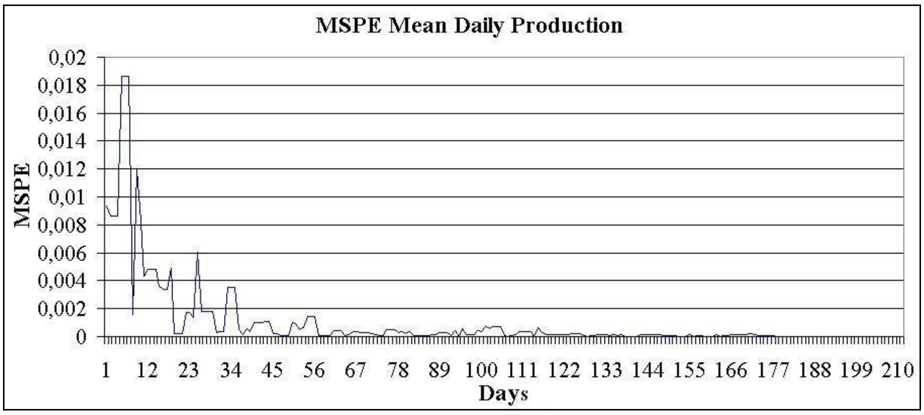


Figure 2.10 – MSpE Analysis

The validation of the simulation model has been conducted using the *Face Validation* method.

Potential users of the model, system experts, compare model and system behaviors under identical input conditions and judge whether the model and its results are reasonable (Balci, 1990).

Also in this case the performance index considered is the mean daily production of each workstation. In order to neglect the effects due to the simulation model warm-up period, the initial values of the real performance index are not considered. Each simulation run has been replicated 5 times. Figure 2.11 shows the mean daily production for the assembly operation.

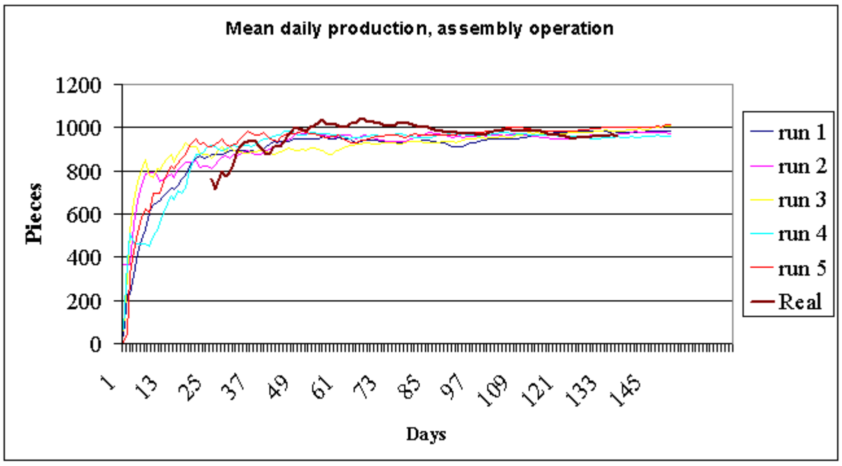


Figure 2.11 – Mean Daily Production for Assembly Operation (real and simulated)

This graph was shown to company experts asking them to make the difference between real and simulated curves. Because of the curves are pretty similar and the experts were unable to make such difference, as a consequence, the model is an accurate representation of the real system. Similar results have been obtained for each department of the manufacturing system.

2.2.5 A what-if analysis on the cut department

The simulation model implemented is used for carrying out what-if analyses and for supporting the manufacturing process management. More in detail, this case study deals with the application of the simulation model for investigating three different operative scenarios of the cut department. Note that the simulation model architecture has been developed including all the required features for using real time the simulator to support the manufacturing process (flexibility, time efficient, interface with the company informative system, etc.).

The three different scenarios being considered are:

- the actual configuration: manual operated cut (*Scenario 1*);
- automatic operated cut (*Scenario 2*);
- manual and automatic operated cut (*Scenario 3*).

Results provided by the simulation model have been analyzed by the company top management taking into consideration both technical efficiency and economic aspects. For example, the amount of money required by the second scenario for buying a completely automated machine capable of respecting the plant mean daily production is higher than the first scenario.

The performance parameters used are:

- the daily production of each productive department;
- the utilization degree of each productive department.

The total number of simulation runs is 3 (one for each scenario). Each simulation run has been replicated 5 times, so the total number of replications is 15 (5x3=15). According to the MSPE analysis each replication has a length of 160 days and requires about 2 minutes of time (so the simulation model real time integration with the system management can be easily justified).

2.2.6 The simulation results analysis

Tables 2.I and 2.II consist of simulation results in terms of utilization degree and daily production of each department. From simulation results analysis the best scenario is the third one characterized by an average utilization degree of 0,75 and an average daily production of 844 units (such values are referred to the entire plant). However, there is a slightly difference between the second and the third scenario. The third scenario performs better because, for some types of hydraulic hoses, the manual cut requires a smaller process time, thus a mixed approach (manual and automated) gives better results. As mentioned earlier, the second scenario requires an high amount of money for buying the automated machine. Further considerations regards the number of workers. In the actual scenario there are two workers, the second scenario requires one worker and the third scenario requires, once again, two workers. Thus the higher amount of money in the second scenario could be balanced in the long period by lower manpower costs.

DEPARTMENT	SCEN.1	SCEN.2	SCEN.3
Preparation	0,80	0,81	0,80
Fittings stamp	0,87	0,87	0,86
Manual Cut	0,97	0,00	0,81
Automated Cut	0,00	0,97	0,71
Skinning operation	0,56	0,86	0,89
Assembly	0,42	0,66	0,67
Junction	0,45	0,69	0,70
Testing operations	0,48	0,73	0,74
Packaging	0,44	0,63	0,63
Average Value	***0,55***	***0,69***	***0,75***

Table 2.I – Utilization Degrees for each scenario

DEPARTMENT	SCEN.1	SCEN.2	SCEN.3
Preparation	931	933	927
Fittings stamp	975	967	956
Manual Cut	510	0	386
Automated Cut	0	994	641
Skinning operation	385	697	703
Assembly	507	974	986
Junction	508	971	1003
Testing operations	512	974	1002
Packaging	519	980	998
Average Value	538	832	844

Table 2.II – Daily production for each scenario

Figures 2.12 – 2.13 graphically report simulation results for two different departments.

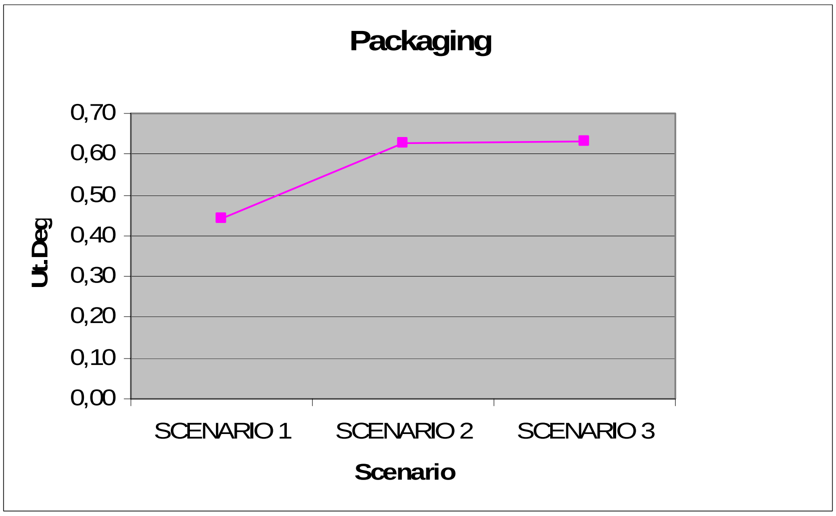


Figure 2.12 – Utilization Degree for Final Controls Operations

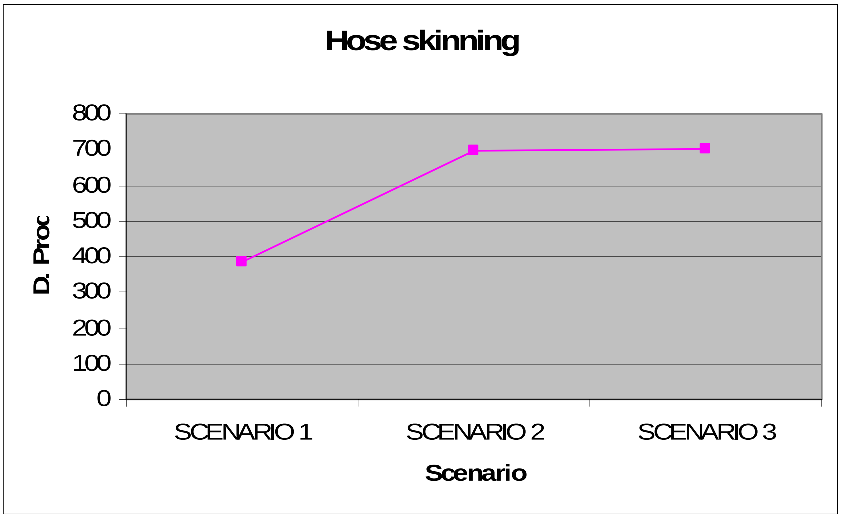


Figure 2.13 – Daily Production for hoses skinning Operations

2.3 The Second Application Example: M&S and Artificial Intelligence for Supply Chain routes analysis

The Supply Chain Management (*SCM*) is a quite complex area; during the last years, the research field related to SCM has received a great deal of attention. SCM is an approach characterized by high level integration for planning and control of material and information flows. As reported in Giannoccaro and Pontrandolfo (2002), SCM literature and studies cover different application fields, like forecasting, procurement, production, distribution, inventory, transportation, and customer service.

In detail, the supply chain (*SC*) is a network of different entities involved in activities and processes at tactical, strategic and operative levels for producing goods according to customers' demand (Iovanella, 2002). In particular, from a production and logistic point of view, SC is a network of resources (distribution centers, plants, retailers and warehouses) having the task to product, store and distribute items to the final market. Each supply chain node is an entity characterized by two critical parameters: the demand and the productive capacity. To meet market demand, SC must guarantee high robustness levels; in other words, in correspondence of market changes, the supply chain has to quickly reconfigure its structure for satisfying customers' demand. SC actors are classified into two groups:

- the *production* agents;
- the *service* agents.

The first group is composed by:

- retailers and wholesalers (where final customers can buy product);
- distribution centers which receive items from production plants, store and deliver them to retailers and wholesalers;
- production plants where goods are produced.

The second group is composed by:

- transport companies which deliver items along the supply chain;
- service companies which provide services connected to supply chain management.

Note that companies operating in the second groups are also known as *third party logistics*.

Each supply chain entity is made up by three elements:

- *internal functions* that include activities and processes required to product items;
- *external upstream elements* which symbolize the operations for purchasing and managing materials and information;
- *external downstream elements* which involve all the operations connected with distribution centers, retailers and wholesalers.

The case study proposed aims at analyzing the supply chain routes by means of artificial intelligence techniques for reducing transportation costs. The lower are the transportation costs, the higher is the customers' satisfaction (*service level*). After the description of the real supply chain and the simulation model, two artificial intelligence techniques are described. Finally, simulation results allow to choose routes characterized by low delivery time and confirm simulation model capability to analyze different operative scenarios.

2.3.1 A Supply Chain operating in the pharmaceutical sector

The supply chain analyzed is made up by 4 suppliers, 1 distribution center and 66 pharmacies. Pharmacies are currently divided in 9 different geographic areas and deliveries in each area are made twice per day by means of trucks. The service level of the SC is related to the rate of the deliveries; as a result, the lower is the time for deliveries, the higher is the service level, the lower are logistic costs.

2.3.2 The Simulation Model of the supply chain

The goal of this application example is to analyze the supply chain routes by means of artificial intelligence techniques for reducing transportation costs. The lower are transportation costs, the higher is the customers' satisfaction (*service level*). On-time deliveries and customers' satisfaction are critical issues when products delivered are medicines.

In detail, after model implementation and its verification/validation, two different artificial intelligence techniques (the ants theory and the genetic algorithms) are implemented to optimize logistic costs and compare results.

The software tool adopted for simulation model implementation is a discrete event-oriented simulation tool, the commercial package eM-Plant™ by *Tecnomatix Technologies* (cfr. Figure 2.14).

Also in this case, during the modeling phase, the classical approach (based on library objects) is replaced by the advanced approach (presented in the previous sections) which consists in storing all the information in tables and using ad-hoc programmed routines in order to implement all the logics and rules governing the system.

The length of each simulation run (24 hours) is fixed and is a consequence of the model and its assumptions while the number of replications, evaluated, during the verification and validation phases is 10.

Figure 2.14 – The Simulation Model Animation

2.3.3 The Artificial Intelligence techniques

According to Dean *et al.* (1995), Artificial Intelligence (*AI*) is an approach for designing and studying computer programs that behave intelligently. From some point of view, AI is the ultimate goal of computer programming. It is important to underline that AI systems need not to be designed to fool a human judge so it is possible to say that the meaning of the terms intelligence in the field of computer remains elusive. In function of its methodologies and purposes, AI can be divided in:

- *weak AI*, which consists in designing computer programs with the intention of adding functionality while decreasing user intervention; an example is represented by many modern word processors which are able to indicate misspelled words without being asked to do so by the user;
- *strong AI*, that is the design of a computer program that may be considered a self-contained intelligence (or intelligent entity); in other words this programs are designed to think in the same way people think.

The AI application is very wide; some of this fields are:

- transportation;
- medicine;
- nuclear application;
- finance;
- insurance;
- robotics;
- safety;
- image processing (recognition, tracking, mapping);
- military operations;
- fraud detection systems;
- scheduling problems;
- medical treatment;
- computer games;
- resource allocation problems.

2.3.3.1 The Ants theory and the Genetic algorithms approaches

As above mentioned, the focus of this case study is to analyze the supply chain routes by means of artificial intelligence techniques, in particular the ants theory and the genetic algorithms, for reducing transportation costs and to compare their capability.

Let us describe synthetically the *ants theory* approach. The importance of this approach is related to its capability in solving optimization problems using the principles of ant colonies, see Dorigo and Blum (2005). From a simulation point of view, an ant colony can be associated to a multi-agent system where the behavior of each agent (*ant*) is defined by simple rules.

The ant colony system behaves in a chaotic and singular way: the basic principle on which the ant algorithms is based is the same of the biologic ants; it consists in the same principle ants use to locate the shortest path from food source to the nest. The applications of this theory are very different; some examples are:

- the traveling salesman problem;
- the vehicle routing problem;
- the problem of graph coloring;
- the quadratic assignment problem;
- the problem of network-traffic optimization;
- the problem of job-shop schedule planning.

The basic principles which characterized ants are:

- ants are social entities living in families or colonies, organized in a perfect way in order to optimize all the activities related to transporting food, overcoming obstacles, building anthills, and other operations;
- ants are self-organized entities: they cooperate from the low-levels to reach the global objective of the system which belong;
- ants are entities able to use only local information and in this case any centralized control is considered out of the system.

In order to transfer information, ants use two different ways:

- a *direct* communication;
- an *indirect* communication

The first one, the direct communication way, includes all the processes related to food exchanges, visual and chemical contacts; the second, the indirect method (also called *stigmergy*), is a particular form of communication when one actor modifies the environment and the others entities involved in the communication process inherit changes made by the first one.

The other approach implemented is the *Genetic algorithms* approach. As reported in Holland (1975), genetic algorithms (*GAs*) are search procedures which reproduce all the processes of natural selection and natural genetics. In particular, GAs differ from other search techniques because their search field consists in a population of points and they use probabilistic rather than deterministic transition rules to solve problems. GAs are ruled by some mechanisms typical of the biological evolution, like:

- reproduction;
- mutation;
- recombination;
- natural selection;
- survival of the fittest.

GAs are implemented in order to reproduce how a population of abstract representations (*chromosomes*) of candidate solutions (*individuals*, *creatures*, *phenotypes*) to an optimization problem evolves in order to obtain the better solution. The starting point of the iterative process is random and the algorithm finishes when a particular number of generations has been reached or when it has been reached a specific fitness level for the population. The application range of this approach is very wide. Some examples are:

- artificial creativity;
- automated design;
- chemical kinetics;
- container loading optimization;
- distributed computer network topologies;
- plant floor layout;
- routes optimization;
- software engineering;
- optimization of data compression systems;
- scheduling applications (job-shop scheduling).

2.3.4 Supply Chain routes optimization

The application example aims at analyzing the pharmaceutical supply chain routes by means of two artificial intelligence techniques (GAs and Ants theory) for reducing transportation costs.

Now the results obtained by means of ants theory approach are described. In particular, a costs analysis on different time intervals (a week, a month, a year) is made by changing generations number (8, 10 and 12 generations are considered). As reported in Figure 2.15, without doubt using the ants theory approach means great gain in terms of delivery costs; for example, for a week these costs decrease from 3600 € before optimization to 3400 € after optimization. In a year these costs decrease from 172300 € to 163200 €, see Figure 2.16.

From the other side, according to Figure 2.17, the GA analysis related to a time period of a week shows that total logistic costs decrease from 4000 € before GAs application to 3700 € after optimization. The same difference comes from the annual costs analysis (the annual costs decrease from 210000 € before GAs application to 190000 € after optimization).

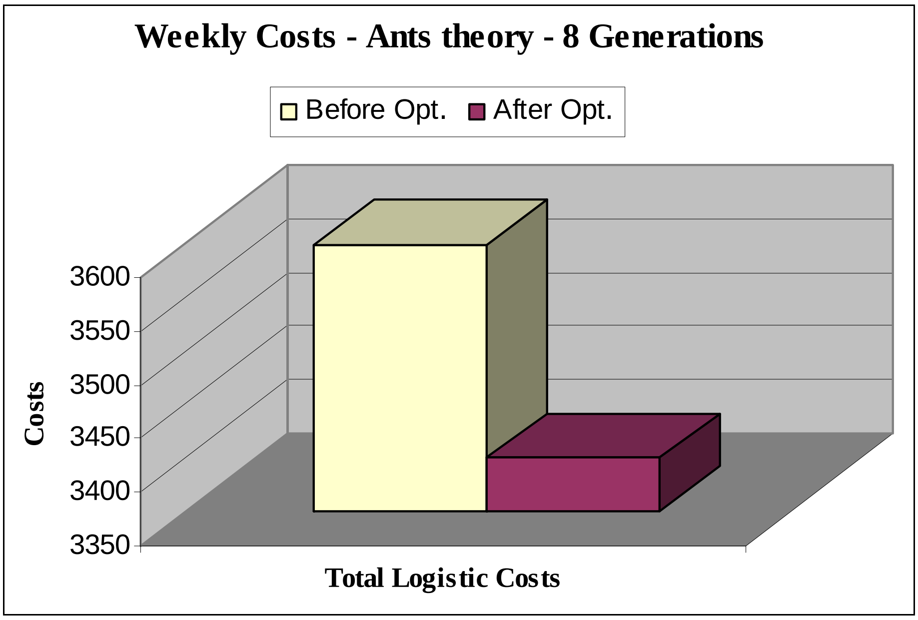


Figure 2.15 – Weekly Costs before and after Ants Theory Optimization

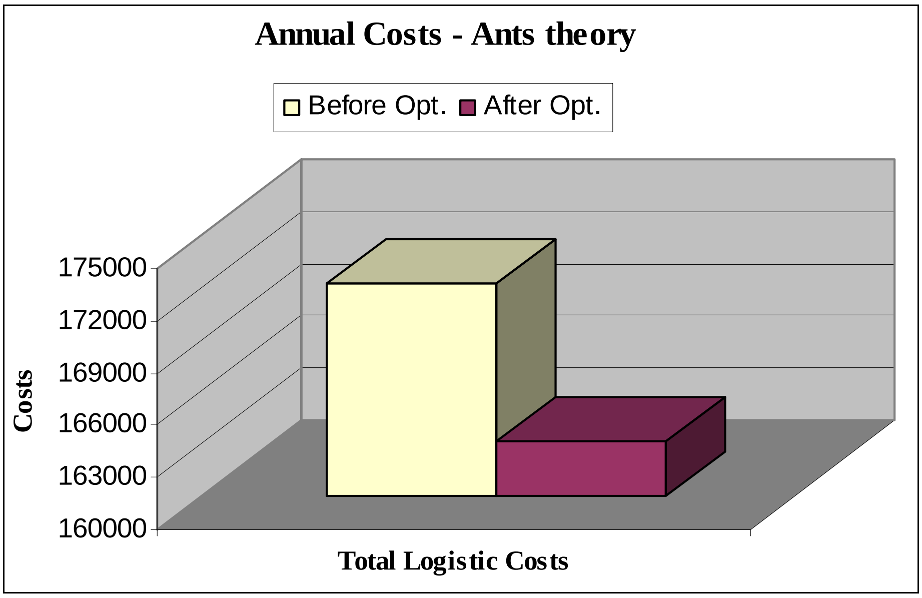


Figure 2.16 – Annual Costs before and after Ants Theory Optimization

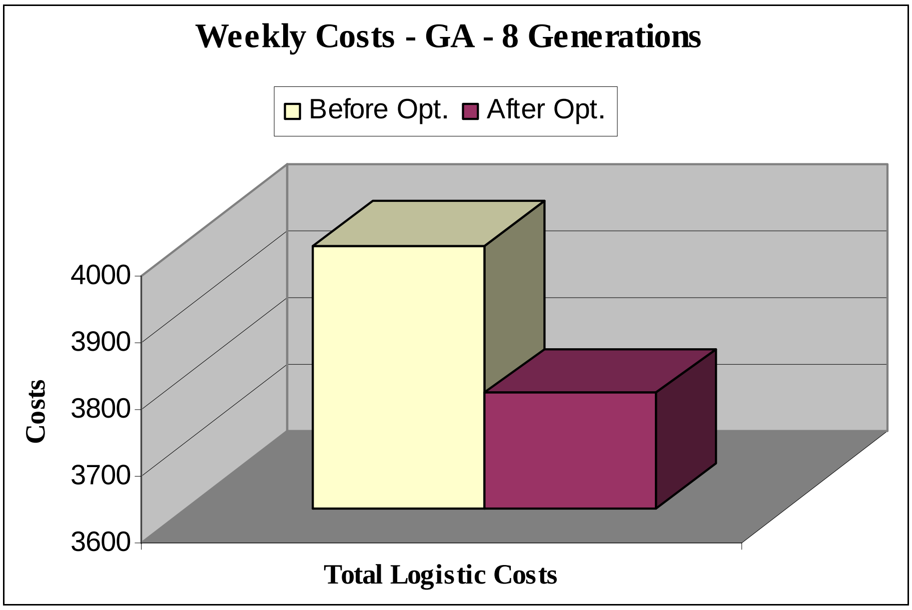


Figure 2.17 – Weekly Costs before and after GA Optimization

According to the results obtained adopting the two theories, it is possible to assert that the ants theory approach works better for a low number of generations; in particular, this approach is good for 8 generations with a difference in terms of weekly costs of about 10%: in fact, the optimal costs evaluated by the ants theory are about 3400 €/week while costs evaluated by GAs approach are about 3770 €/week, see Figure 2.18. From the other side, the genetic algorithms approach gives results which in correspondence of 10 generations are better than those obtained by the ants theory. As reported in Figure 2.19, from GAs approach, weekly costs are about 3200 € whereas the costs obtained with the ants theory approach are about 3600 €.

For a larger number of generations, the difference between the two approaches is negligible, see Figure 2.20.

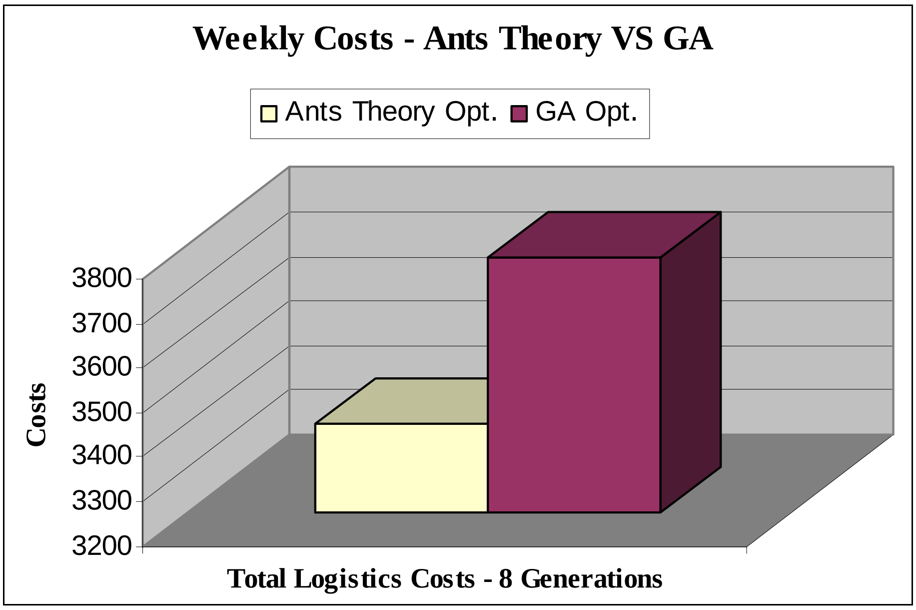


Figure 2.18 – Weekly Costs Comparison between Ants Theory and GA results for 8 Generations

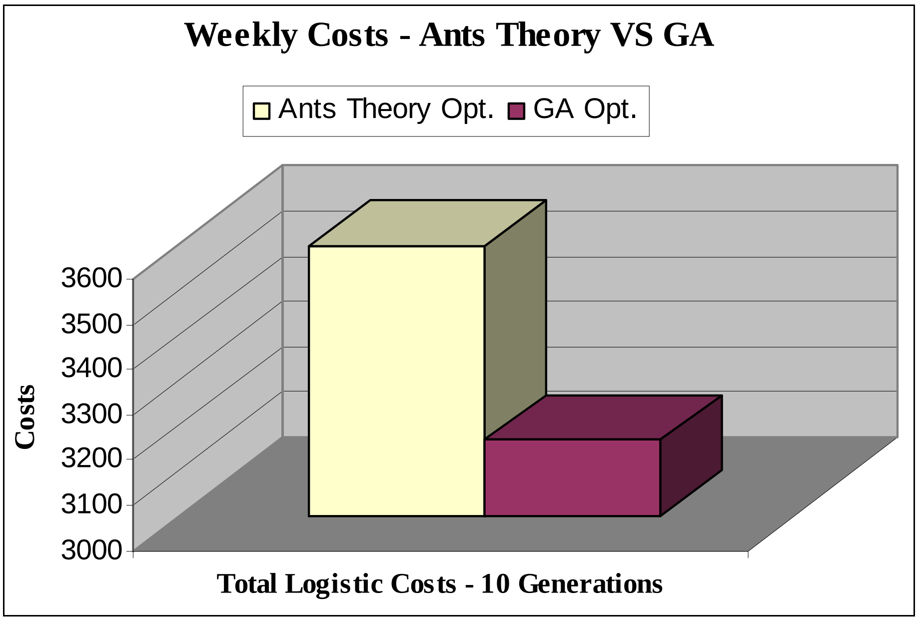


Figure 2.19 – Weekly Costs Comparison between Ants Theory and GA results for 10 Generations

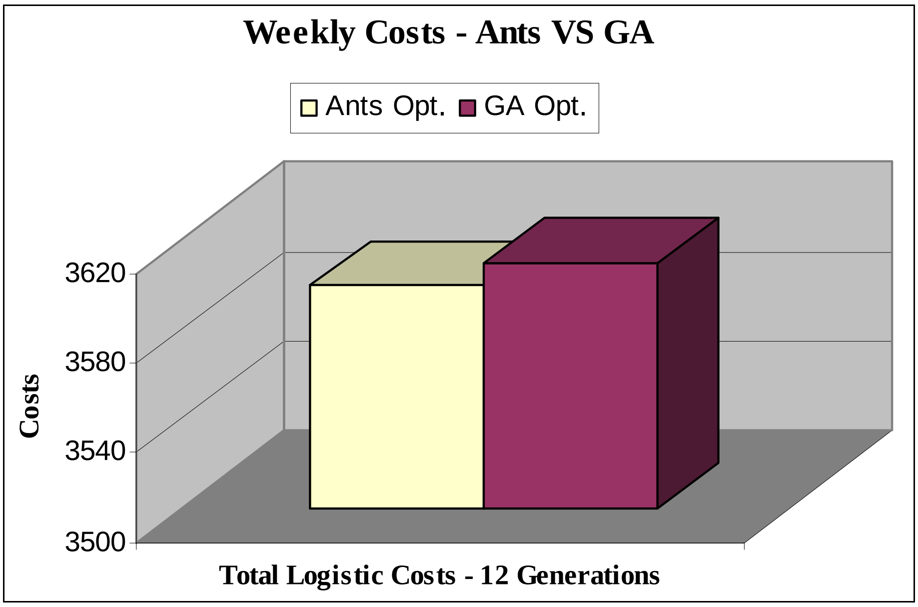


Figure 2.20 – Weekly Costs Comparison between Ants Theory and GA results for 12 Generations

2.4 Conclusions

A successful simulation study requires huge experience as well as a long training phase to acquire correctly M&S principles and statistical techniques for input and output data analysis. To this end, the first part of the PhD course was devoted to develop two applications examples (in two different areas, manufacturing and supply chain) with the aim of facing the main problems and critical issues in developing a simulation study.

The first application example deals with a what-if analysis for testing the performance of a real manufacturing system under three different operative configurations. The second application example concerns the implementation of a simulation model which reproduces all the activities of a real supply chain operating in the pharmaceutical field. Analysis conducted are based on the comparison of two artificial intelligence techniques for reducing transportation costs.

References

Balci, O., 1990. Guidelines for successful simulation studies. *Proceedings of the 1990 Winter Simulation Conference*, 9-12 December, Piscataway, New Jersey (USA), 25-32.

Banks, J., 1998. Handbook of Simulation. John Wiley & Sons, Inc.

Berry, W.L., 1972. Priority scheduling and inventory control in a job shop lot manufacturing systems. *AIIE Transactions*, 4, 267-276.

Callahan, R.N., Hubbard, K.M., Bacoski, N.M., 2006. The use of simulation modelling and factorial analysis as a method for process flow improvement. *Advanced Manufacturing Technology*, 29, 202-208.

Dean, T., Allen, J., Aloimonos, Y., 1995. Artificial Intelligence: theory and practice. Addison Wesley.

Dorigo, M., Blum, C., 2005. Ant colony optimization theory: a survey. *Theoretical Computer Science*, 344 (2), 243-278.

Erenguk, S., Vakharia, A.J., 1999. Integrated production/distribution planning in supply chains. *Operational Research*, 115, 219-236.

Forza, C., 1996. Achieving superior operating performance from integrated pipeline management: An empirical study. *Physical Distribution and Logistics Management*, 26 (9), 36-63.

Fujimoto, R., 1999. Parallel and distributed simulation. *Proceedings of the 1999 Winter Simulation Conference*, 5-8 December, Squaw Peak, Phoenix (AZ), 122-131.

Giannoccaro, I., Pontrandolfo, P., 2002. Inventory management in supply chains: a reinforcement learning approach. *Production Economics*, 78, 153-161.

Holland, J.H., 1975. Adaptation in Natural and Artificial Systems.

Iovanella, A., 2002. Introduzione alla supply chain management. 4-7.

Korhonen, H.M., Heikkila, J., Tornwall, J.M., 2001. A simulation case study of production planning and control in printed wiring board manufacturing. *Proceedings of the 2001 Winter Simulation Conference*, 9-12 December, Arlington, Virginia (USA), 844-847.

Karacal, S.C., 1998. A novel approach to simulation modeling. *Computers & Industrial Engineering*, 34 (3), 573-587.

Longo, F., Mirabelli, G., Papoff, E., 2005. Material flow analysis and plant lay-out optimization of a manufacturing system. *International Journal of Computing*, 1 (5), 107-116.

Mullarkey, P., Gavirneni, S., Morrice, D.J., 2000. Dynamic output analysis for simulations of manufacturing environments. *Proceedings of the 2000 Winter Simulation Conference*, 10-13 December, Orlando, Florida (USA), 1290-1296.

Nunnikhoven, T.S., Emmons, H., 1977. Scheduling on parallel machines to minimize two criteria related to job tardiness. *AIIE Transactions*, 3, 288-296.

Stenger, A.J., 1996. Reducing inventories in a multi-echelon manufacturing firm: a case study. *Production Economics*, 45, 239-249.

Stevens, G., 1989. Integrating the supply chain. *Physical Distribution & Materials Management*, 19 (8), 3-8.

Terzi, S., Cavalieri, S., 2004. Simulation in the supply chain context: a survey. *Computers in Industry*, 53, 3-16.

Thomas, D.J., Griffin, P.M., 1996. Coordinated supply chain management. *Operational Research*, 94 (1), 1-15.

CHAPTER 3

The Inventory Management Policies

3.1 Introduction

The objective of this chapter is twofold: (i) firstly we present some new inventory control policies, (ii) then we propose different case studies to test the capability of the inventory control policies to store efficiently inventory in different nodes of the supply chain for satisfying customers' service level and other metrics related to supply chain efficiency.

Supply chains nodes (i.e. manufacturing systems) and supply chain networks behavior are investigated (by using ad-hoc simulation models) under the effects of different constraints related to demand intensity, variability and lead times. This enables us to carry out a comprehensive set of analyses in order to test the proposed inventory control policies.

3.2 The Inventory Management Policies

Before starting to describe the mathematical model for each inventory control policy, let us introduce the following notation (where *i* refers to the *i-th* item and *t* is the time):

- $s_i(t)$, the re-order level at time t for the item *i*;
- $S_i(t)$, the target level at time t for the item *i*;
- $SS_i(t)$, the safety stock level at time t for the item *i*;
- $Di(t)$, demand at time *t* for item *i;*
- $DF_i(t)$, the demand forecast at time t for the item *i*;
- *ST,* safety time for safety stock evaluation;
- $OHI_i(t)$, the on-hand inventory at time t for the item *i*;
- $OQ_i(t)$, the quantity already on order at time t for the item *i*;
- $SQ_i(t)$, the quantity to be shipped at time t for the item *i*;
- $Q_i(t)$, the quantity to be ordered at time t for the item *i*;
- $T_i(t)$, the review period of the item *i;*
- $L_i(t)$, the lead time of the item *i;*
- $DFL_i(t)$, the demand forecast over the lead time for the item *i*;
- $IP_i(t)$, the inventory position at time t for the item *i*.

Decision to place an order for the item *i* is made on the basis of the Inventory Position, defined as reported in equation 3.1

$$IP_i(t) = OH_i(t) + OQ_i(t) - SQ_i(t) \tag{3.1}$$

3.2.1 The modified Re-Order-Point, Order-Quantity *(sQ)* policy

This inventory control policy is derived from the classical inventory policy, but differs from it because it takes into consideration the stochastic component of the demand. In fact, the reorder point $s_i(t)$ is evaluated as sum of the demand forecast over the lead time and the safety stock. The demand forecast over the lead time is evaluated by using the single exponential smoothing methodology (Sylver *et al.*, 1998). Equation 3.2 allows to evaluate the demand forecast at time t for the item i while equation 3.3 allows to evaluate the demand forecast over the lead time for the item i.

$$DF_i(t) = \alpha * D_i(t-1) + (1-\alpha) * \sum_{k=t-1-Hd}^{t-1} D_i(k) / Hd \tag{3.2}$$

$$DFL_i(t) = \sum_{j=t}^{t+LT} DF_i(j) \tag{3.3}$$

- α : single exponential smoothing parameter;
- *Hd*: number of periods considered as historical data for evaluating the lead time demand.

The Safety Stock is inventory that is stocked to protect against uncertainties (i.e. uncertainties related to production and/or transportation problems, suppliers' problems, etc.) and usually has a remarkable effects the service level provided to final customers. In our case the Safety Stock cover the demand deviation over a certain period defined as Safety Time (*ST*). We assume that the *ST* is the same for all the items and it is defined as follows.

$$ST = L_i + q * \sigma_{LT} \tag{3.4}$$

where:

- q is a standard deviation factor (the greater is q the higher is the service level provided to final customers);
- σ_{LT} is the standard deviation of the lead time.

As before mentioned the Safety Stock is evaluated as standard deviation of the Demand over the Safety Time. Equation 3.5 evaluates the standard deviation of the daily demand at time t.

$$\sigma_i(t) = \sqrt{\frac{\sum_{t}^{t+M-1} D_i^2(t) - \left(\sum_{t}^{t+M-1} D_i(t) \right)^2 / M}{M-1}} \tag{3.5}$$

with:

- M number of period considered for the evaluation of the standard deviation of the daily time demand.

Finally, equation 3.6 allows to evaluate the Safety Stock as standard deviation of the Safety Time Demand.

$$SS_i(t) = \sigma_i(t) * ST \tag{3.6}$$

The reorder point $s_i(t)$ is:

$$s_i(t) = DFL_i(t) + SS_i(t) \tag{3.7}$$

If $IP_i(t)$ falls below the $s_i(t)$, a fixed quantity will be ordered (equation 3.8). The quantity to be ordered can be defined using the Economic Order Quantity (*EOQ)* method (Sylver *et al.*, 1998).

$$Q_i(t) = EOQ_i(t) \tag{3.8}$$

3.2.2 The modified Order-Point, Order-Up-To-Level *(sS)* policy

As described in Chapter 1, this policy is characterized by two parameters:

- $s_i(t)$, the re-order level at time t for the item i;
- $S_i(t)$, the target level at time t for the item i.

We modified this policy introducing a new constant parameter, $K_i(t)$, which represents the average daily demand of the item i so the equations expressing $s_i(t)$ and $S_i(t)$ are as follows:

$$s_i(t) = DFL_i(t) + SS_i(t) \tag{3.9}$$

$$S_i(t) = s_i(t) + K_i(t) \tag{3.10}$$

Equations 3.11 and 3.12 respectively express the re-order condition and the quantity to be ordered.

$$IP_i(t) < s_i(t) \tag{3.11}$$

$$Q_i(t) = S_i(t) - IP_i(t) = s_i(t) + K_i(t) - IP_i(t) \tag{3.12}$$

The evaluation of $Q_i(t)$ requires the calculation of the demand forecast ($DFL_i(t)$) according to equations 3.2 and 3.3.

3.2.3 Continuous review with re-order level equals to target level and constant safety stock *(sS,1)* policy

In this policy the re-order level $s_i(t)$ is equal to the target level $S_i(t)$ and the safety stock is kept constant. Equation 3.13 defines the re-order and target levels, equation 3.14 defines the order condition, while equation 3.15 defines the quantity to be ordered.

$$s_i(t) = S_i(t) = DFL_i(t) + SS_i \tag{3.13}$$

$$IP_i(t) < s_i(t) = S_i(t) = DFL_i(t) + SS_i \tag{3.14}$$

$$Q_i(t) = S_i(t) - IP_i(t) = DFL_i(t) + SS_i - IP_i(t) \tag{3.15}$$

Equations 3.13, 3.14 and 3.15 clearly show that in this policy an order is placed whenever the inventory position (diminished by the lead time demand) drops below the constant safety stock (evaluated just once as the standard deviation of the lead time demand).

3.2.4 Continuous review with re-order level equals to target level and variable safety stock *(sS,2)* policy

This policy is based on policy presented in section 3.2.3 (sS,1), however the Safety Stock in function of time and evaluated by using equations 3.4, 3.5 and 3.6. The conditions related to the purchase order emission and the quantity to be ordered are defined by equations 3.16 and 3.17.

$$IP_i(t) < s_i(t) = S_i(t) = DFL_i(t) + SS_i(t) \tag{3.16}$$

$$Q_i(t) = S_i(t) - IP_i(t) = DFL_i(t) + SS_i(t) - IP_i(t) \tag{3.17}$$

3.2.5 Continuous review with fixed evaluation period *(sS,3)* policy

According to this policy, the reorder level, the target level and the safety stock are supposed to be constant over the evaluation period *RP* (after this time interval the reorder level, the target level and the safety stock are recalculated).

If $RPD_i(t)$ is the demand forecast over the evaluation period (evaluated using a similar procedure used for the lead time demand and safety time demand), it is possible to assert that:

$$s_i(t) = L_i * \frac{RPD_i(t)}{RP} + SS_i(t) \tag{3.18}$$

$$S_i(t) = \frac{RPD_i(t)}{RP} + s_i(t) \tag{3.19}$$

The Safety Stock is evaluated according to equations 3.4, 3.5 and 3.6. An order must be placed according to equation 3.20 while the quantity to be ordered is defined by equation 3.21.

$$IP_i(t) < s_i(t) \tag{3.20}$$

$$Q_i(t) = S_i(t) - IP_i(t) \tag{3.21}$$

3.2.6 Continuous review with optimized evaluation period *(sS,4)* policy

This policy is based on policy presented in section 3.2.5 *(sS,3)*, however the evaluation period is kept changing with respect to time and optimized with respect to inventory costs. For the inventory costs description, the following notation is adopted:

- $C_{i,o}$, order placing cost for item *i*;
- $C_{i,t}$, transportation cost for item *i*;
- $C_{i,r}$, order reception cost for item *i*;
- $C_{i,st}$, storage cost for item *i*;
- $C_{i,w}$, worsening cost for item *i*;
- $C_{i,ob}$, obsolescence cost for item *i*;
- $C_{i,i}$, interest cost for item;
- P_i, price for the item *i*.

The total cost for purchase order emission is calculated by using equation 3.22 and the total cost for storage is evaluated through equation 3.23.

$$TC_{POE,i} = C_{i,o} + C_{i,t} + C_{i,r} \tag{3.22}$$

$$TC_{ST,i} = C_{i,st} + C_{i,w} + C_{i,ob} + C_{i,i} \tag{3.23}$$

The optimized evaluation period, $ORP_i(t)$, is calculated minimizing, on the basis of demand forecast, the unitary inventory cost $UIC_i(t)$, that is:

$$UIC_i(t) = \frac{TC_{POE,i} + TC_{ST,i} * \sum_{t}^{t+T-1} (t-1) * DF_i(t)}{\sum_{t}^{t+T-1} DF_i(t)} = MIN \tag{3.24}$$

The value of *t* that minimizes $UIC_i(t)$ is the optimized evaluation period $ORP_i(t)$. If $ORPD_i(t)$ is the forecast demand over the optimized evaluation period (calculated using a similar procedure used for the lead time demand and safety time demand) the reorder level and the target level can be calculated using equations 3.25 and 3.26.

$$s_i(t) = DFL_i + SS_i(t) \tag{3.25}$$

$$S_i(t) = ORPD_i(t) + s_i(t) \tag{3.26}$$

More in detail, the $ORPD_i(t)$ is the optimal lot size calculated by means of demand forecast. The first term of the sum in equation 3.26 is recalculated every $ORP_i(t)$ days whilst the second term is recalculated every day. The emission condition of the purchase order and the quantity to be ordered follow the equation 3.20 and 3.21.

In the sequel two different case studies will be presented; in particular we look at the behavior of the inventory control polices presented above both in manufacturing systems (one case study) and supply chains (one case study). The main idea is to provide relevance on the potentials of the inventory control policies by testing their capabilities (in terms of performance metrics) in real contexts and under the effects of different constraints (mostly related to demand intensity, demand variability and lead times). To this end an approach based on Modeling & Simulation (M&S) is used for modeling the whole complexity of real scenarios (in order to be able to look into details of all processes and activities that take place within a manufacturing system or supply chain). For each case study all the steps of the simulation study are presented (also providing the reader with an accurate description of the manufacturing system or supply chain considered).

3.3 The Inventory Management in a manufacturing system devoted to produce high pressure hydraulic hoses

The manufacturing system being analyzed produces high pressures hydraulic hoses and it is located in Calabria, southern of Italy. The manufacturing system and the simulation model have already been presented in Chapter 2 (refer to Section 2.2). According to company top management requests, we decided to integrate the initial simulation model with a Web-based Inventory Management system for testing the efficiency of policies presented in sections 3.2.1 to 3.2.6 (*(sQ)*, *(sS)*, *(sS,1)*, *(sS,2)*, *(sS,3)* and *(sS,4)*) to store inventory (in terms of fill rate and on hand inventory). In particular section 3.4 will compare the *(sS,1)*, *(sS,2)*, *(sS,3)* and *(sS,4)* inventory control policies, while section 3.5 will compare the *(sQ)* and *(sS)* inventory control policies.

According to Coyle *et al.* (1992), product availability is the most important element for increasing customer service level (fill rate). The main tool to control product availability is the Master Production Schedule (*MPS*). In fact, the critical inputs of a Material Requirement Planning (MRP) system are (Silver *et al.*,1998):

- the Master Production Schedule (*MPS*) which is a time-phased plan of quantities and activities needed to produce each item;
- the Bill of Materials (*BOM*) which is a list of all the raw materials, parts, subassemblies needed to assemble an item;
- the Inventory Database (*ID*) in order to monitor the inventory level of each part of the final product for a detailed stock monitoring because the MRP system, in contrast with traditional replenishment approaches, is formulated in order to keep lower the inventory level;
- information related to outstanding or planned replenishment orders;
- forecasts of demand for each component;
- production or procurement lead times for each process/operation;
- possible scrap allowances for some operations.

Figure 3.1 displays the conceptual model of the system implemented. As shown in this figure, the key-role of the application is represented by the MPS which contains all the information related to production scheduling; it is also linked with the suppliers internal system and with the simulation model from which is updated in case of suppliers delays.

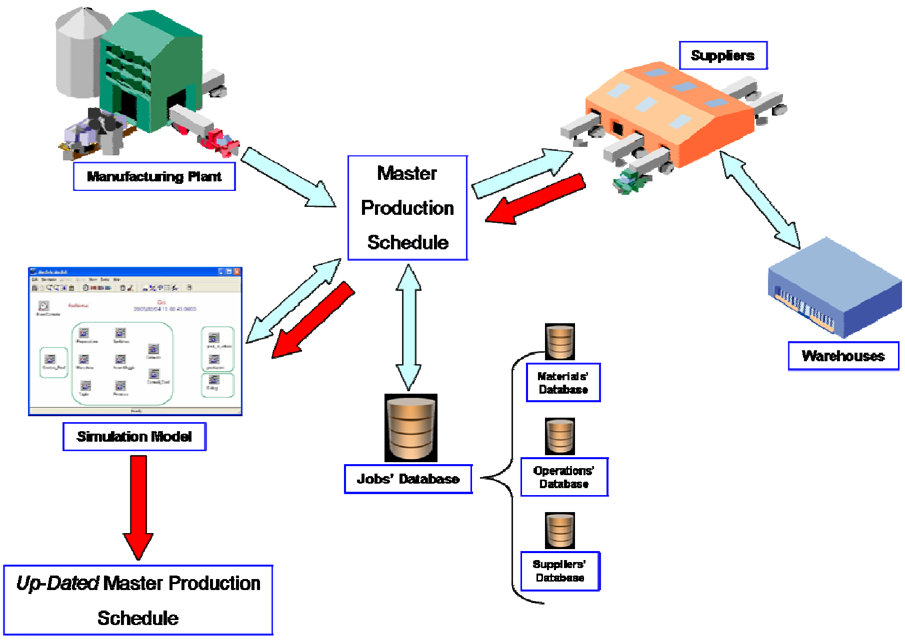


Figure 3.1 – The conceptual model of the system

3.4 *(sS,1)*, *(sS,2)*, *(sS,3)* and *(sS,4)* behavior investigation and comparison

In this first case study the inventory control policies presented in sections 3.2.3, 3.2.4, 3.2.5 and 3.2.6 are compared. In particular the policies are:

- continuous review with re-order level equals to target level and constant safety stock *(sS,1)*;
- continuous review with re-order level equals to target level and variable safety stock *(sS,2)*;
- continuous review with fixed evaluation period *(sS,3)*;
- continuous review with optimized evaluation period *(sS,4)*;.

Simulation runs were carried out considering different scenarios in terms of customers' demand intensity, customers' demand variability and lead times. Note that the final customer is completely satisfied if the Shop Order is completed before the due date. Delays in Shop Orders completion, due to stock outs or materials unavailability, causes the reduction of the service level provided to customers. A correct comparison of different inventory control policies requires the same initial base for each policy. To this end the service level provided to customers is kept constant in each scenario being analyzed.

More in detail, three different operative scenarios have been implemented in order to compare inventory control policies behavior and find the optimal inventory control policy:

- *first scenario*: average on-hand inventory versus demand intensity;
- *second scenario*: average on-hand inventory versus demand variability;
- *third scenario*: average on-hand inventory versus lead time.

The results comparison allows to understand which policy performs better in terms of average on hand inventory keeping fixed the service level provided to customers.

3.4.1 Scenarios definition and simulation run length

Table 3.I defines the different scenarios analyzed by using the simulation model presented in Chapter 2 (Section 2.2). For each inventory control policy, we consider three different scenarios in terms of demand intensity, demand variability and lead times. Before using the simulation model for carrying out the scenarios analysis, the length of the simulation run and the number of replications for each run need to be evaluated. To this end, the Mean Square Pure Error analysis (*MSpE*) has been used.

Scenario 1			
Demand intensity	Low	Medium	High
Demand variability	Medium		
Lead time	Medium		
Scenario 2			
Demand intensity	Medium		
Demand variability	Low	Medium	High
Lead time	Medium		
Scenario 3			
Demand intensity	Medium		
Demand variability	Medium		
Lead time	Low	Medium	High

Table 3.I – Scenarios Definition

The MSpE analysis allows to evaluate the optimal length of the simulation run. As known from literature, the simulation run has to be long enough to guarantee significant statistical results. In this case, the statistical results regard the average on-hand inventory. The MSpE can be evaluated by using the equation 3.27 and choosing as initial simulation run length T=300 days.

$$MSPE(t) = \frac{\sum_{j=1}^{n}\left[y_j(t) - y(t)\right]^2}{n-1} \quad (3.27)$$

with:

- t, time (expressed in days);
- $n=5$, number of replications;
- $y_i(t)$, the values of the on hand inventory;
- $y(t)$, the mean value of the n observations collected at the instant of time t regarding the on hand inventory.

The time-evolution of the curve, obtained over 5 replications, shows that after 160 days the MSpE can be neglected (the error is lower than 5%), consequently the simulation run has been chosen equal to 160 days.

3.4.2 The simulation results analysis and *(sS,1)*, *(sS,2)*, *(sS,3)*, *(sS,4)* comparison

In this section a detailed description of simulation results in correspondence of each scenario of Table 3.I is presented. For each scenario, three simulation runs (replicated 5 times, with length 160 days as required by the MSpE analysis) have been carried out. In effect, the combination medium demand volume, medium demand variability and medium lead time is carried out only for the first scenario. Totally 35 (7x5) replications have been carried out. The average on hand inventory is evaluated at the end of each simulation run.

First Scenario – Average on -hand inventory versus demand intensity

The first scenario consists in comparing the four inventory control policies in correspondence of different demand volumes (keeping constant both demand variability and lead times).

Figure 3.2 shows the behavior of the inventory control policies in terms of on-hand inventory keeping fixed the service level provided to stores (approximately 95% for low volume, 85% for medium volume and 75% for high volume demand).

The average on-hand inventory comparison in correspondence of low demand volume shows that the continuous review policy with fixed evaluation period *(sS,3)* and the continuous review policy with optimized evaluation period *(sS,4)* have a similar performance; the continuous review with constant safety stock *(sS,1)* performs better than the continuous review with variable safety stock *(sS,2)*. Differences in volume of the customers' demand drastically affect the on-hand inventory. In correspondence of medium volume the average on-hand inventory goes down and the *(sS,4)* starts to perform better than the *(sS,3)*. Once again, the *(sS,1)* performs better than the *(sS,2)*. Let us now consider high demand volume. The difference among *(sS,3)* and *(sS,4)* policies, in terms of average on-hand inventory, increases as well as the difference between *(sS,1)* and *(sS,2)*. Note that the difference, in terms of average on-hand inventory, between the best policy and the worst policy in correspondence of high demand volume is greater than the same difference in correspondence of low demand volume. In other words the *(sS,3)* and the *(sS,4)* improve their performance as the volume of customers' demand increases.

Second Scenario – Average on-hand inventory versus demand variability

Let us consider the second scenario: comparison of the four inventory control policies in correspondence of different levels of demand variability (keeping constant both customers' demand volume and lead times). The trend of the average on-hand inventory for each control policy is shown in Figure 3.3. The on-hand inventory comparison in correspondence of low variability shows that the *(sS,4)* policy performs better than the *(sS,3)* policy; the continuous review with constant safety stock *(sS,1)* performs better than the continuous review with variable safety stock *(sS,2)*. As in the previous case, different demand variability levels affect the average on-hand inventory. A larger fluctuation of the demand variability causes higher average on-hand inventory (the inventory could be not available at the right time to be fully used for the on going Shop Orders).

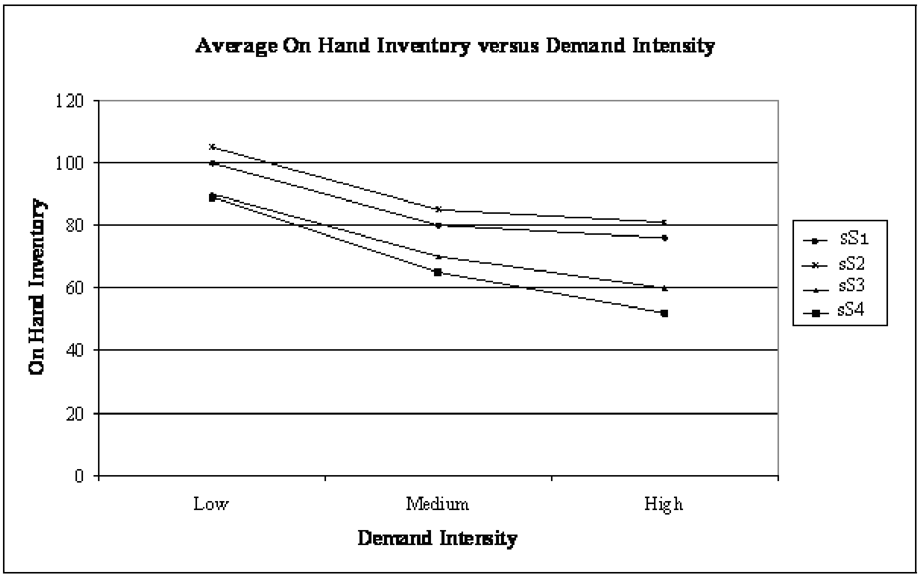


Figure 3.2 – Average on-hand inventory versus demand intensity

In effect, in correspondence of medium demand variability level the average on-hand inventory is slightly higher than the previous case. The evaluation period based policies are capable of achieving the same fill rate with lower average on-hand inventory than the other policies. Once again, the constant safety stock performs better than the variable safety stock and the optimized evaluation period works better than the constant review period.

The average on-hand inventory still increases in correspondence of high demand variability level as well as the inventory policies show a behavior similar to the previous case. Note that the higher is the demand variability levels the lower is the capability of the evaluation period based policies to achieve low values of average on-hand inventory. The difference, in terms of average on-hand inventory, between the best policy and the worst policy in correspondence of high variability is smaller than the same difference in correspondence of low variability.

Third Scenario – Average on -hand inventory versus Lead Time

The third scenario compares the average on-hand inventory achieved by the inventory control policies in correspondence of low, medium and high lead times (keeping fixed demand volume and variability). Figure 3.4 shows the trend of the average on-hand inventory for each inventory control policy.

The average on-hand inventory increases in correspondence of medium and high lead times (for all the inventory control policies). As in the previous case the policies based on evaluation period work quite better than the continuous review policies, furthermore the *(sS,4)* and *(sS,1)* policies respectively perform better than the *(sS,3)* and *(sS,2)* policies. Note that the higher is the lead time, the lower is the capability of the evaluation period based policies to achieve low values of average on-hand inventory. The difference, in terms of average on-hand inventory, between the best policy and the worst policy in correspondence of high lead time is slightly smaller than the same difference in correspondence of low lead time.

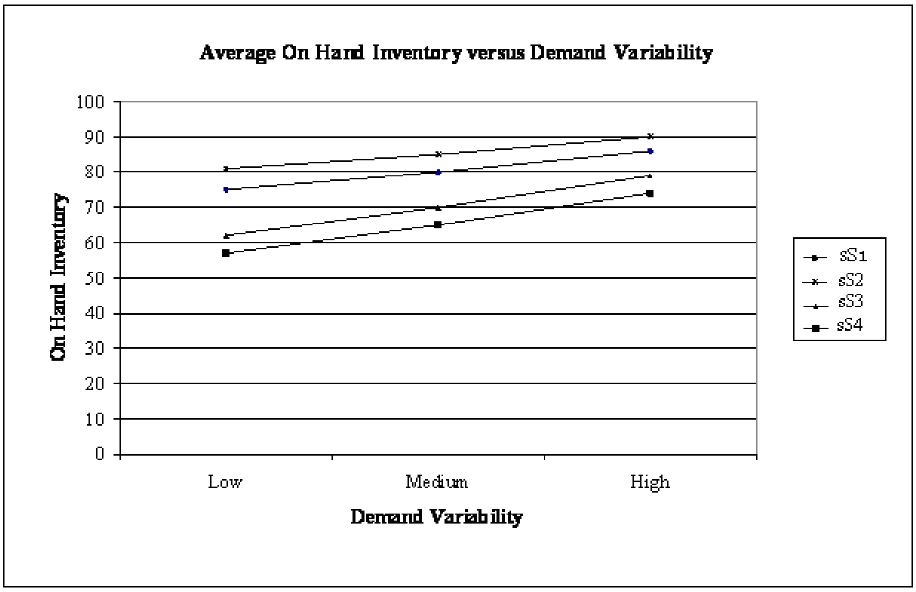


Figure 3.3 – Average on-hand inventory versus demand variability

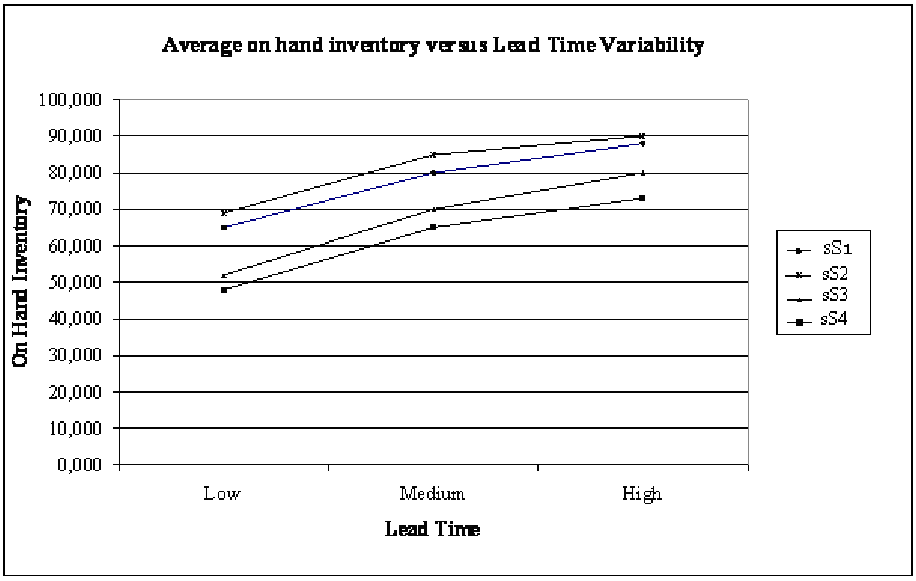


Figure 3.4 – Average on-hand inventory versus lead time

3.5 *(sQ)* and *(sS)* behavior investigation and comparison

In this section we are going to compare the remaining inventory control policies:

- the modified Re-Order-Point, Order-Quantity *(sQ)* policy;
- the modified Order-Point, Order-Up-To-Level *(sS)* policy.

These policies are compared considering three different values of lead times (respectively 1-2-3 days), defined according to suppliers' delivery plan; these values are in fact provided by suppliers at the end of the day through a web interface (they access the MPS to control if their delivery plan satisfy manufacturing plant production requirements for each Shop Order). All the data, organized in specific databases, are input data for the simulator.

As already pointed out in section 3.4.1 the optimal simulation run length is 160 days. For comparing the *(sQ)* and *(sS)* inventory control policy and monitoring, at the same time, the manufacturing system performance, two parameters are considered:

- the average on-hand inventory (*OHI*) for each inventory control policy;
- the mean daily production of each productive department and of the whole production plant;

There are two scenarios, one for each inventory policy. Each scenario needs 3 simulation runs because the lead time assumes three values (1-2-3 days). Each simulation run has been replicated 4 times, so the total number of replications is 24 (2x3x4=24).

3.5.1 The simulation results analysis and *(sQ)* and *(sS)* comparison

In this section, results provided by the simulation model are analyzed. Figure 3.5 shows a comparison of the two inventory control policies taking into consideration the OHI level.

As shown in Figure 3.5, for a supplier lead time of 3 days the OHI level for each policy is greater than the OHI for lead time of one day and for lead time of 2 days. Manufacturing system performance has been also monitored taking into consideration the mean daily production of each productive department in function of each inventory control policy in order to analyze how suppliers' lead times variation affects the productivity of each system department. Results of this analysis are proposed in Figure 3.6-3.7.

Figure 3.8 shows a comparison between the two policies in function of the mean daily production of all the productive departments and lead times.

Each policy works better for a lead time of one day. In fact, considering, for example, the *(sS)* policy, it is simple to see that the mean daily system production decreases when the supplier lead times increase. From the other side, comparing the two inventory policies, it is possible to underline that the *(sS)* policy works better than the *(sQ)* policy guaranteeing a greater mean daily production level.

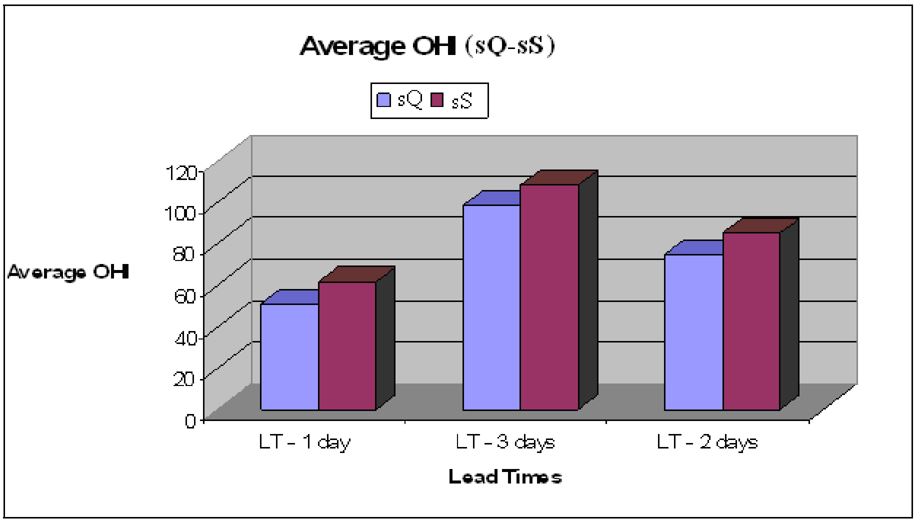


Figure 3.5 – Average on-hand inventory for sQ-sS policies

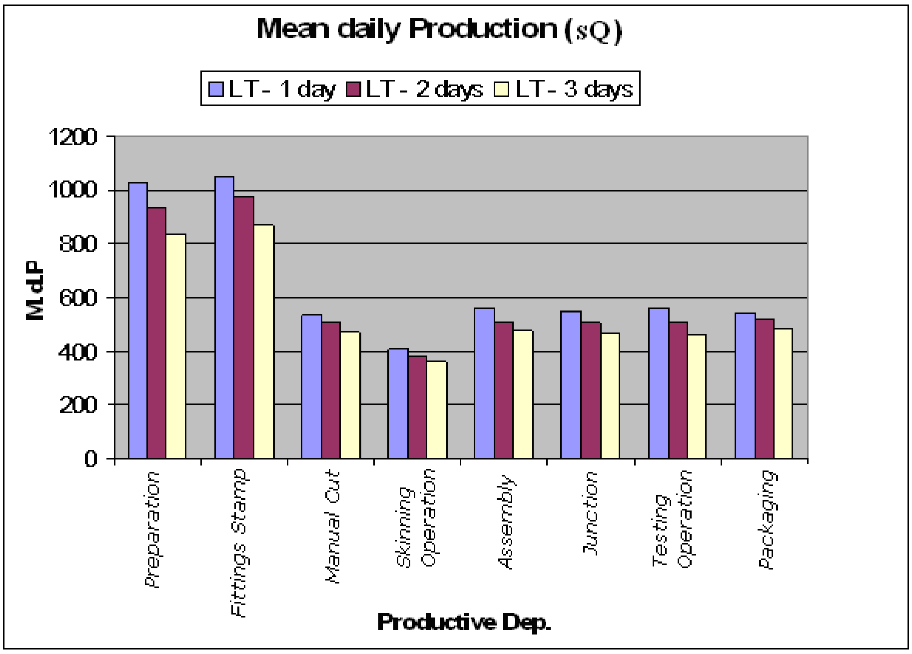


Figure 3.6 – Mean daily production – sQ policy

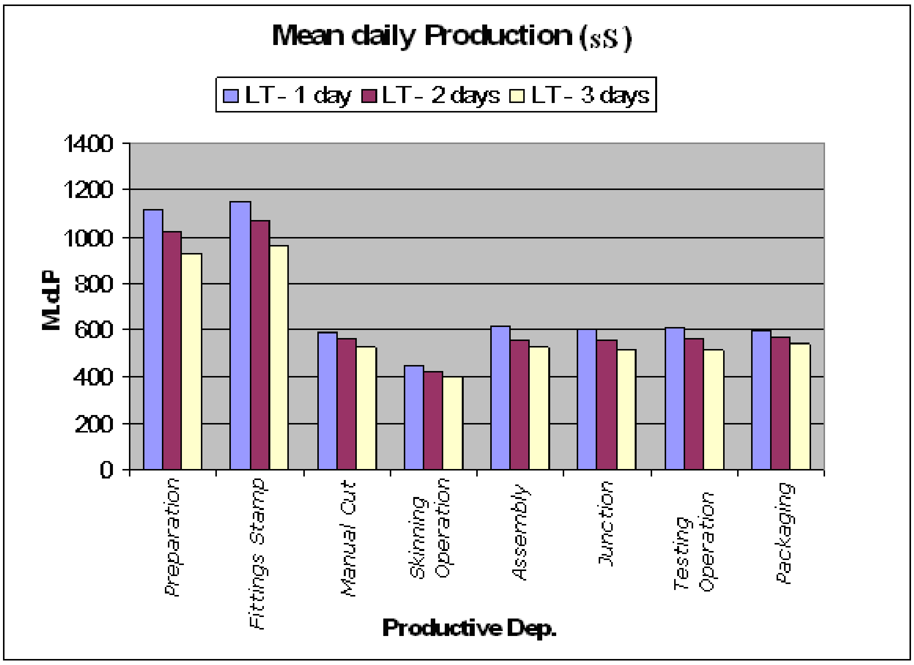


Figure 3.7 – Mean daily production – sS policy

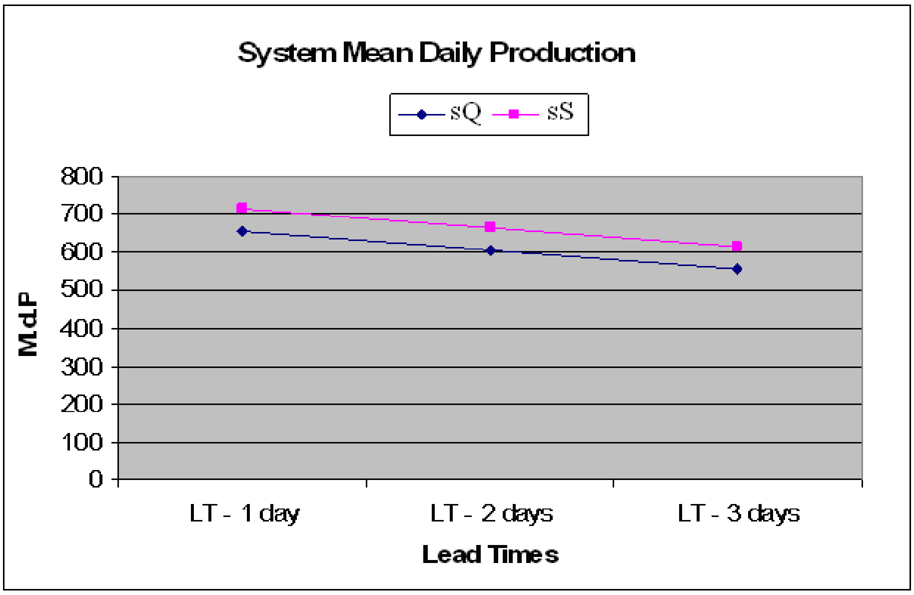


Figure 3.8 – Mean daily production for different lead times

3.6 The Inventory Management in a three-echelons Supply Chain

In the remaining part of the chapter we are going to look at the behavior of the inventory control polices in a three echelon supply chain operating in the beverage sector. Starting from the actual supply chain configuration, a detailed study of the inventory systems is proposed. The test of a comprehensive set of different operative scenarios, in terms of customers' demand intensity, customers' demand variability and lead times, becomes a powerful tool for inventory systems analysis along the supply chain. The main objective is the comparison of optimistic and pessimistic scenarios for studying the behavior of the different inventory control policies and optimizing the inventory system of each supply chain node. Due to the dynamically changing and stochastic behavior of the supply chain variables as well as the complex interactions among its actors, we have been pushed to implement an advanced supply chain simulation model.

3.6.1 The conceptual model of the Supply Chain

The SC is made up by three echelons (as shown in Figure 3.9) each one including the following nodes:

- *M* manufacturing plants (*MPs*);
- *N* distribution centers (*DCs*);
- *J* stores or retails (*STs*).

Product demand is defined by the final customer.

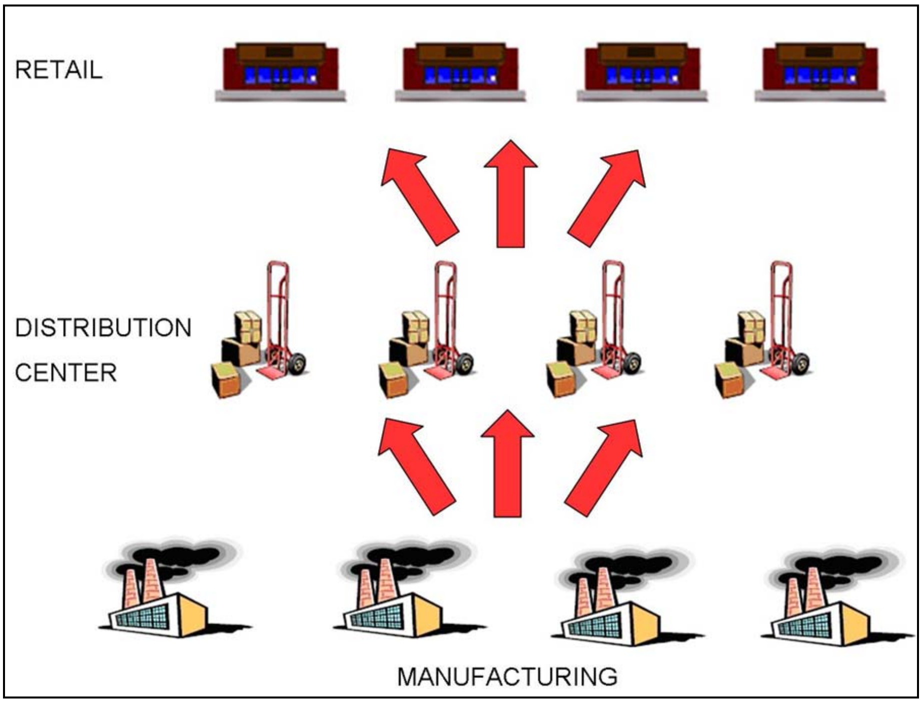


Figure 3.9 – The conceptual model of the Supply Chain

Each manufacturing plant has *K* identical processes and it is equipped to manufacture *I* different types of products.

Variables characterizing the manufacturing plants are:

- the set-up time (different for each plant and for each product);
- the processing time dependent on order size;
- the production capacity.

The second SC level is made up by *N* DC, which stores all the *I* products. The inventory control within each DC is as follows. When an order arrives to a DC, the current inventory position (on-hand inventory plus the quantity already on order minus the quantity to be shipped, see equation 3.1) is checked. If the order is fully satisfied, its status is considered completed and, as a consequence, the inventory level of the DC is decreased of the order quantity, otherwise a lost quantity is recorded. The most important performance measures within a DC are the number of fully satisfied and partially satisfied store orders per period, the total lost sales quantity per period to define the service level and the fill rate. From an internal logistics point of view, processes and activities carried out within the DCs depend on layout design, storage assignments methods, routing methods, order batching and zoning. According to ELA/AT Kearney (2004), DCs are warehouses in which activities related to storage, buffering and distribution of raw materials, good-in-process, finished products are executed.

The third SC level is represented by stores. Each ST works on an 8-h shift. At the beginning of the day, an inventory review is made at each store to decide about an order emission at one of the *N* DCs. Note that, according to this policy, store orders are delayed until the beginning of the next day so order replenishment is guaranteed by the DC the following day. Each store chooses the DC capable of replenishing the maximum order quantity requested. The quantity to order for each product is defined by checking the current on-hand inventory at the store. At each ST, number of fully or partially satisfied orders, lost sales quantity and total quantity ordered for each product are recorded. These data are then used for performance measure evaluation (e.g., the service level, fill rate, etc.).

3.7 The Simulation Model of the Supply Chain

The simulation model is implemented using the commercial simulation software *Plant Simulation*™ by UGS. This software allows the creation of computer simulation models related to material flow, resource utilization and logistics for all levels of plant planning from global production facilities, through local plants, to specific lines to explore their features and to optimize their performance.

In particular, an advanced modeling approach is adopted for the simulation model development: the classical modeling approach based on library objects to reproduce static and dynamic entities (material flow, machines, production line, etc.) is replaced with an advanced one that replaces entities flow with a flow of information stored in tables. To access, update and record such information stored in tables, ad hoc programmed routines have been implemented. The modeling approach proposed has the advantage to allow high flexibility levels in terms of simulation model modifications (to reproduce several system behaviors under different operative conditions). Note that the main disadvantage of the modeling approach being used is the animation: generally animation reproduces the entities flow within the simulation model; in this case, the animation is not considered a priority aspect of the simulation study even if model structure allows animation implementation (see Chapter 2 for further details).

3.7.1 The Manufacturing Plants model implementation

This section of the simulation model recreates the manufacturing plants and the items production process. If all the machines of a plant are busy when an order arrives, this order is queued waiting for another available resource. The switch from a product type to another requires a set-up time. According to a make-to-order system, no warehouses are available at each plant. DCs select plants to send the order on the basis of the lead time and quantity that the plant can refurbish. Figure 3.10 shows the block diagram of the MP selection process.

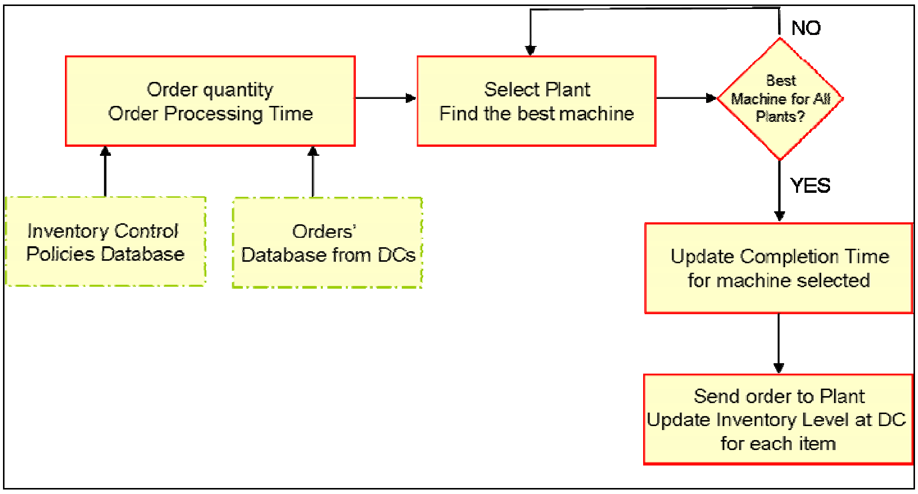


Figure 3.10 – Block diagram for the manufacturing plant selection

The simulation model first evaluates total process times and set-up times, then selects the best machine in each plant (capable of processing the order in the shortest time) and finally the best machine among all the plants. The selection of the best machine is made according to the time required for completing queued orders and starting the new order.

3.7.2 The Distribution Centers model implementation

The section of the simulation model recreates the DCs and implements all the logics related to the inventory control policies and the internal logistics management. In effect, the simulation model of the DC recreates a real DC that supports stores activities within the beverage sector. The most important processes and activities implemented within the distribution center model regard:

- trucks arrival and departure for items deliveries (from industrial plants and toward stores);
- forklift and lift trucks for material-handling operations;
- performance measures control and monitoring (number of items handled, material-handling systems utilization, inventory logistics costs, waiting times for suppliers' and retailers' trucks).

The process related to orders management is the following: at the beginning of the day, the purchase orders from stores arrive at the DCs. The model checks the inventory levels to verify if incoming orders can be satisfied. In each DC, items number of incoming orders is compared with the on-hand inventory level. If there is enough on-hand inventory, STs demand is totally satisfied and the on-hand inventory level is updated; if demand is partially satisfied or unsatisfied, lost sales are recorded. Each DC emits purchasing orders towards the manufacturing plant on the basis of demand forecast. The main activities that take place within each DC are summarized by the block diagram in Figure 3.11.

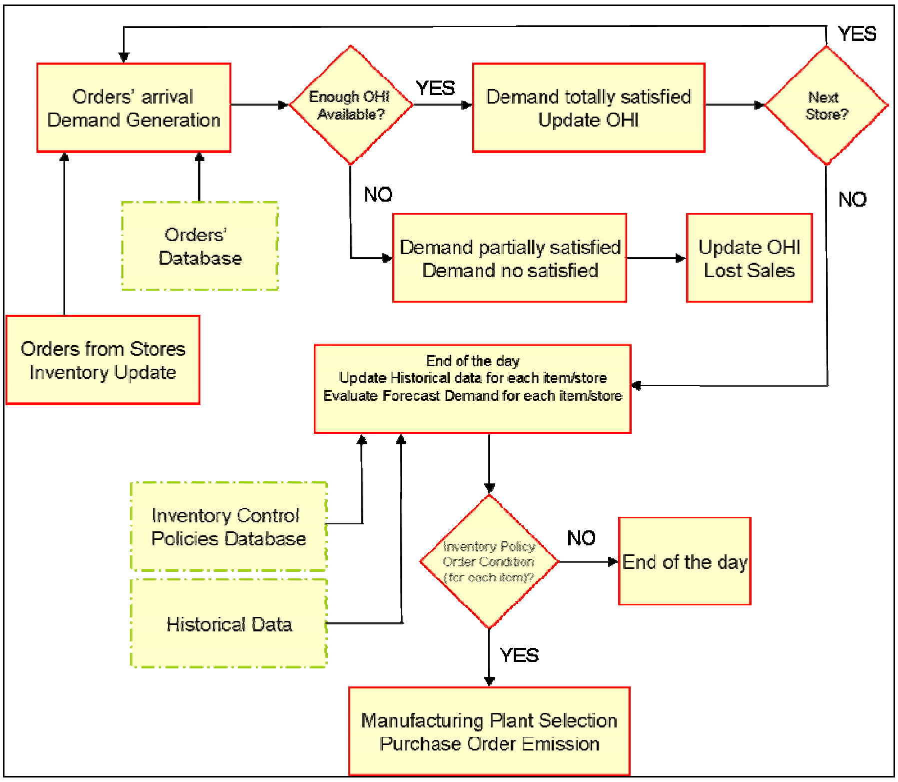


Figure 3.11 – The Distribution Centers Block diagram

3.7.3 The Stores model implementation

In terms of orders management, the activities performed within each ST are quite similar to the activities performed within the DCs so the simulation model implementation is approximately the same. In effect, at the end of the day, the inventory level is checked to evaluate whether a purchase order has to be emitted.

The block diagram in Figure 3.12 describes the activities performed by the simulation model within each store.

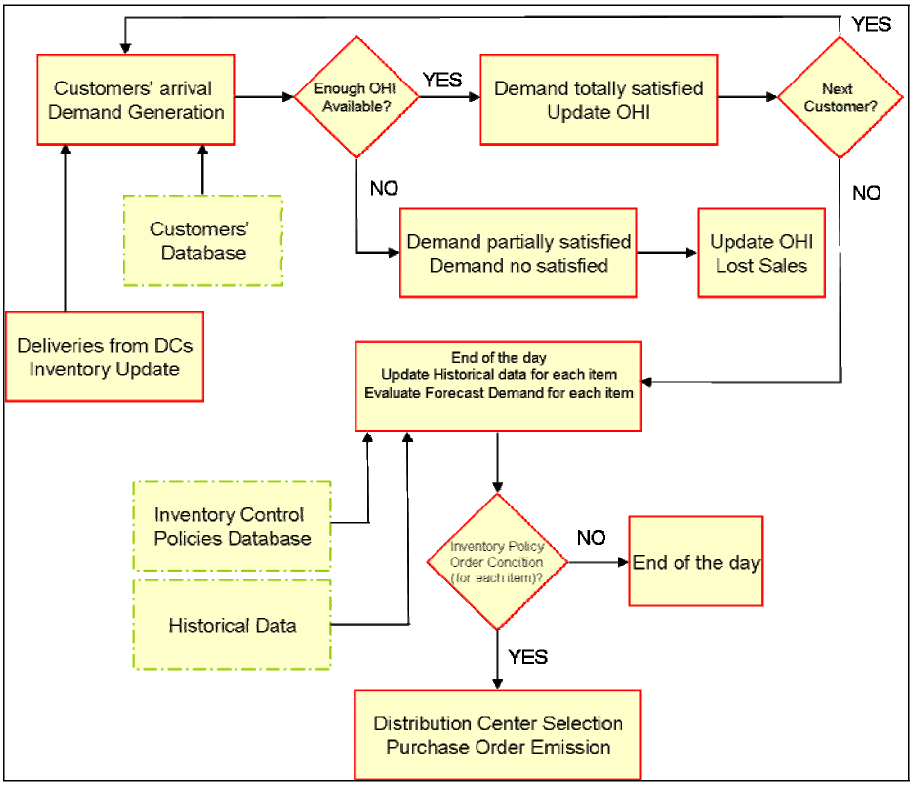


Figure 3.12 – The Stores Block diagram

3.7.4 Supply chain simulation model Verification and Validation

The simulator verification has been made using a dynamic technique (debugging). As explained in Dunn (1987), Debugging is an iterative process that aims to find model errors and to improve the model correcting the errors. The model is tested for revealing the presence of bugs. The causes of each bug must be correctly identified. The model is opportunely modified and tested (once again) for ensuring errors elimination as well as for detecting new errors. All the methods (routines written in Simple++) have been iteratively debugged line by line, detecting and correcting all the errors. Errors detected during the simulation study life cycle were due to: misunderstanding or numerical error on input data, tables and spreadsheet indexes management, events list organization and management. In addition, before model translation, all the logics governing supply chain have been discussed with supply chain experts.

Before getting into details of simulation model validation, we need to speak about the simulation run length. The length of a simulation run is an information used for validation, for design of experiments and simulation results analysis. Such length is the correct trade-off between results accuracy and time required for executing the production runs. The run length has been correctly determined using the mean square pure error analysis (MS_{PE}).

As well known the mean square of the experimental error must have a knee curve trend. As soon as the simulation time goes by, the standard deviation of the experimental error (due to statistic and empirical distributions implemented in the simulation model) becomes smaller. The final value has to be small enough to guarantee high statistical result accuracy. Note that, in this case, the experimental error is referred to two supply chain performance measures (fill rate and average on hand inventory).

Consider that the performance measures are calculated for each supply chain node, thus, the MSPE analysis has to be repeated for each supply chain node and for each performance measure. The MSPE curve that takes the greatest simulation time for obtaining negligible values of the mean squares defines the simulation run length. Figure 3.13 shows the overlapping of the fill rate MSPE curves of distribution centre #2 that takes the greatest simulation time. After 400 days the MSPE values are negligible and further prolongations of the simulation time do not give significant experimental error reductions.

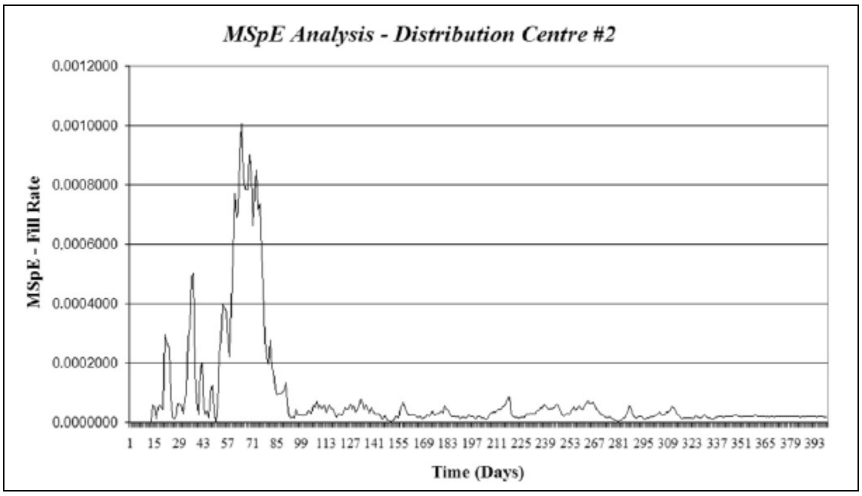


Figure 3.13 – The MSpE Analysis

Choosing for each simulation run the length evaluated by means of MS_{PE} analysis (400 days) the validation phase has been conducted using the *Face Validation* (informal technique). For each retailer and for each distribution centre the simulation results, in terms of fill rate, have been compared with real results. The plot has been shown to supply company's experts asking to make the difference between the real curve and the simulated curves on the basis of their estimates (obviously showing contemporarily all the curves). The experts weren't unable to make such difference, testifying the validation of the simulation model. The Face Validation technique has been applied for the remaining retailers as well as for each distribution centre. Further results in terms of fill rate confidence intervals have been analyzed. We concluded that, in its domain of application, the simulation model recreates with satisfactory accuracy the real system.

3.8 *(sQ)*, *(sS)* and *(sS,3)* behavior investigation and comparison along the supply chain

In this section the inventory control policies presented in sections 3.2.1, 3.2.2 and 3.2.5 are compared. In particular the policies are:

- the modified Re-Order-Point, Order-Quantity *(sQ)* policy;
- the modified Order-Point, Order-Up-To-Level *(sS)* policy;
- the continuous review with fixed evaluation period *(sS,3)* policy.

The main idea is to investigate and compare the behavior of the above mentioned control policies along the supply chain and considering, in each supply chain node, two different performance measures: the fill rate and on-hand inventory. The fill rate is defined as the ratio between the number of fully satisfied orders and the total number of orders received by the supply chain node. The on hand inventory is the actual quantity of items available in the warehouse.

The inventory control policies behavior investigation and comparison is supported by simulation experiments according to factors and levels reported in Table 3.II. Note that the values of lead times, demand intensity and demand variability are expressed as percentage of the actual values.

Factors	***L1***	***L2***	***L3***
Lead Time	90%	100%	110%
Demand Intensity	90%	100%	110%
Demand Variability	90%	100%	110%

Table 3.II – Factors and levels for inventory control policies comparison along the supply chain

3.8.1 Scenarios definition

Simulation results, for each factor levels combination, are expressed in terms of average fill rate and on-hand inventory. Simulation results are available for each store and for each DC of the SC, even if we are going to present the most significant results obtained for one of the distribution center. The following scenarios have been investigated:

- comparison of the 90%, 100% and 110% scenarios in terms of demand intensity;

- comparison of the 90%, 100% and 110% scenarios in terms of demand variability;
- comparison of the 90%, 100% and 110% scenarios in terms of lead times.

3.8.2 The simulation results analysis

For each scenario, the behavior of the inventory control policies is investigated. Table 3.III reports the simulation results in terms of fill rate for the first scenario.

Scenarios	***(sS)***	***(sQ)***	***(sS,3)***
90% Demand Intensity	0.831	0.641	0.890
100% Demand Intensity	0.499	0.210	0.539
110% Demand Intensity	0.282	0.058	0.295

Table 3.III – Fill rate comparison (for each inventory control policy) under different demand intensity

The best results in terms of fill rate are provided by the *(sS,3)* inventory control policy; the lowest value by the *(sQ)* inventory control policy. Note that the higher the demand intensity the lower is the fill rate (for each inventory control policy). In addition for high demand intensity, the *(sS)* and the *(sS,3)* inventory control policies show similar behaviors in terms of fill rate values. Table 3.IV shows the simulation results in terms of on-hand inventory for the first scenario.

Scenarios	***(sS)***	***(sQ)***	***(sS,3)***
90% Demand Intensity	100	113	54
100% Demand Intensity	105	121	69
110% Demand Intensity	154	194	134

Table 3.IV – On-hand inventory comparison (for each inventory control policy) under different demand intensity

Concerning the on-hand inventory, the *(sS,3)* performs better than the other policies.

Table 3.V reports the simulation results in terms of fill rate for the second scenario.

The *(sQ)* inventory control policy gives the worst performance. Note the similar behavior of the *(sS)* and *(sS,3)* policies. The policy based on the evaluation period shows a better behavior in correspondence of low demand variability (in effect the higher the demand variability the higher is the demand forecast error).

Scenarios	(sS)	(sQ)	(sS,3)
90% Demand Variability	0.511	0.219	0.569
100% Demand Variability	0.496	0.205	0.533
110% Demand Variability	0.487	0.190	0.520

Table 3.V – Fill rate comparison (for each inventory control policy) under different demand variability

The best policy in the case of low demand variability is the *(sS,3)*; in the case of the actual demand variability *(sS)* and *(sS,3)* show similar behaviors. Finally, in the case of high demand variability, *(sS,3)* allows to obtain the highest fill rate values. Table 3.VI reports the simulation results in terms of on-hand inventory for the second scenario.

Scenarios	(sS)	(sQ)	(sS,3)
90% Demand Variability	101	112	67
100% Demand Variability	104	113	69
110% Demand Variability	111	117	73

Table 3.VI – On-hand inventory comparison (for each inventory control policy) under different demand variability

Concerning the on-hand inventory, once again, the *(sS,3)* performs better than the other policies.

Table 3.VII reports the simulation results in terms of fill rate for the third scenario.

Scenarios	(sS)	(sQ)	(sS,3)
90% Lead Time	0.510	0.247	0.544
100% Lead Time	0.496	0.205	0.533
110% Lead Time	0.447	0.152	0.526

Table 3. VII – Fill rate comparison (for each inventory control policy) under different demand variability

Such scenario investigates the effect of different lead times on the fill rate. Note that the higher the lead time the lower is the fill rate (for each inventory control policy). The fill rate reductions passing from 90% to 100% lead time and from 100% to 110% are as follows:

- 1.1% and 3.9% for the *(sS)* inventory control policy;
- 3.3% and 4.2% for the *(sQ)* control policy;
- 0.9% and 0.5% for the *(sS,3)* control policy.

Consequently, the *(sS,3)* policy performs better than *(sS)* and *(sQ)*.

Table 3.VIII reports the simulation results in terms of on-hand inventory for the third scenario.

Scenarios	*(sS)*	*(sQ)*	*(sS,3)*
90% Lead Time	84	92	50
100% Lead Time	104	113	69
110% Lead Time	121	121	78

Table 3. VIII – On-hand inventory comparison (for each inventory control policy) under different demand lead times

The results above presented regard one of the supply chain distribution center. The analysis of each scenario allows to evaluate the behavior of the inventory control policies as well as to find out the best performance of the inventory systems in terms of fill rate and average on hand inventory. The new scenarios are compared with the actual scenario in terms of what-if analysis. Similar results have been obtained for each supply chain node, both stores and distribution centers, analyzing and optimizing the inventory systems along the supply chain.

3.9 Conclusions

The first part of the Chapter presents and defines six inventory control policies; then two different case studies (one in the manufacturing area and one in the supply chain area) are presented. To provide relevance on the potentials of the inventory control policies to store efficiently the inventory, on both case studies a simulation model is used for investigating and comparing inventory control policies behavior under different constraints in terms of demand intensity, demand variability and lead times.

In the first case study a simulation model of a manufacturing system devoted to produce high pressures hydraulic hoses (located in Calabria, southern of Italy) is presented. The simulation model has been integrated with a Web-based Inventory Management system for testing the efficiency of all the inventory control policies presented in the initial part of the Chapter. In particular, firstly the *(sS,1)*, *(sS,2)*, *(sS,3)* and *(sS,4)* inventory control policies are compared and then a specific analysis (also monitoring the production efficiency of each manufacturing system department) is carried out considering the *(sQ)* and *(sS)* inventory control policies.

In the second case study a real three echelons supply chain operating in the beverage sector has been considered. Due to its stochastic behaviour, the supply chain has been studied using an advanced Modelling & Simulation based approach supported by a well planned design of experiments. The initial phases of the study have required a strong cooperation with supply chain managers for correctly defining the conceptual model, for input data collection, for model translation, verification and validation. Having obtained a simulation model that recreates with satisfactory accuracy the real supply chain, we conducted a comprehensive investigation of the *(sS)*, *(sQ)* and *(sS,3)* inventory control policies along the supply chain under different demand patterns and lead times constraints.

References

Banks, J., 1998. Handbook of Simulation. John Wiley & Sons, Inc.

Coyle, J.J, Bardi, E.J., Langley, C.J., 1992. The Management of Business Logistics. West Publishing Company, New York.

ELA/AT Kearney, 2004. Excellence in Logistics 2004. ELA, Brussels.

Longo, F., Mirabelli, G., 2008. An advanced supply chain management tool based on modelling and simulation. Computer and Industrial Engineering, 54 (3), 570-588.

Silver, E.A., Pyke, D.F., Peterson, R., 1998. *Inventory Management and Production Planning and Scheduling*. John Wiley & Sons, USA.

CHAPTER 4

Warehouse Management

4.1 Introduction

Warehouses play a critical role in logistic systems and supply chains: they are places where firms store raw materials, semi-finished or finished products (Coyle *et al.*, 2003). According to Lambert and Stock (1993), a warehouse has to guarantee:

- *movements* necessary to store products properly which can be distinguished into: movements of inbound goods from transportation carriers to quality and quantity controls; movements from the receiving area to specific locations of the warehouse; movements of outbound goods from the warehouse to customers;
- *storage* which consists in storing products necessary for inventory replenishment (*temporary storage*) or for safety/buffer stocks (*semi-permanent storage*);
- *information transfer* related to products inventory and throughput levels, customers' data, facility space utilization and also about the personnel in order to monitor and manage all the warehouse activities.

Bloomberg *et al.* (2002) classify warehouses into three types:

- *private* warehouses employed by firms for storing their goods until deliveries or sales (Bloomberg *et al.*, 2002). Moreover, private warehouses allow to maintain the physical control of products demand over the facility (Coyle *et al.*, 2003);
- *public* warehouses are employed by companies without large inventory accumulations or a very seasonal need for warehousing space or in the case of products to be delivered in small quantities for long distances. In other words, public warehousing allows to avoid capital investment and financial risks and increase warehousing flexibility (Coyle *et al.*, 2003);
- *contract* warehouses are a particular type of public warehousing and they are adopted in case of seasonal products, geographic coverage requirements, flexibility in testing new marketing strategies and reductions in transportation costs (Bloomberg *et al.*, 2002).

During the last years several research works has been developed in the field of warehouse management and internal logistics planning and control (Van den Berg, 1999).

Gudehus (1973), Hausman (1976), Graves (1977) and Schwarz (1978) discuss of these topics for the first time because in the 1970s interests in management moves from productivity improvement to inventory reduction. Nowadays inventory reduction is favored by both the continuous development of computer technology, which enables these improvements through Electronic Data Interchange (*EDI*) and software systems such as the Enterprise Resources Planning (*ERP*) systems and Warehouse Management systems (*WMS*) and by advanced methodologies such as the Materials Requirement Planning (*MRP*) and Just in Time (*JIT*) manufacturing, see Van den Berg (1999).

Before introducing planning and control activities, according to Anthony (1965), management decisions can be distinguished in:

- *strategic* decisions are long-term decisions aiming at the definition of those policies which support the competitive strategies of a company, i.e. supply chain organization and warehouse design;
- *tactical* decisions are related to an efficient material and work scheduling by taking into consideration all the constraints defined by strategic decisions, i.e. products storage and assignment, deliveries modes, shipments arrivals, etc.;
- *operational* decisions are short-term decisions due to strategic and tactical decisions.

Ashayeri and Gelders (1985) provide a review of the warehouse design models while Hariga and Jackson (1996) propose a review of the inventory models.

As a consequence, an efficient inventory management has to reduce the inventory levels and to improve all the warehouse operations and processes. Moreover, because of strategic decisions are long-term decisions, they are characterized by a high uncertainty level so stochastic models are needed. Literature presents several case study showing the advantages of intelligent planning and control policies application, see Van Oudheusden *et al.* (1988), Frazelle *et al.* (1994), Brynzer *et al.* (1995).

The state of art overview highlights that very often models proposed are not able to recreate the whole complexity of a real warehouse system (including stochastic variables, huge number of items, multiple deliveries, etc).

This Chapter presents the simulation model of a real warehouse operating in the large scale retail sector.

The simulator, called WILMA (*Warehouse and Internal Logistics Management*) has been developed under request of one of the major Italian company operating in the large scale retail sector.

After a description of the real warehouse, Section 2 introduces the simulation model implementation and its verification and validation while Section 3 discusses its application for warehouse design and resources and costs analysis. Finally, conclusions are presented in Section 4.

4.2 The Warehouse System

As before mentioned, the warehouse belongs to one of the most important company operating in the large scale retail sector and it is characterized by:

- a surface of 13000 m^2;
- a shelves' surface of 5000 m^2;
- a surface for packing and shipping processes of 3000 m^2;
- a surface for unloading and control operations of 1800 m^2;
- three levels of shelves;
- eight types of products;
- a capacity in terms of pallets of 28400 pallets;
- a capacity in terms of pallets for each product of 3550 pallets;
- a capacity in terms of packages of about one million packages.

Figure 4.1 shows the warehouse layout.

Figure 4.1 – The Real Warehouse Layout

4.3 WILMA: warehouse and inventory management

According to De Koster *et al.* (2007), warehouses represent an important part of a firm logistics system because of their function to store or buffer products (raw materials, goods-in-process, finished products).

We propose an approach based on Modeling & Simulation for exploring and experimenting possibilities in order to evaluate system behavior under internal/external changes.

In particular, according to warehouse managers' and company experts' requests (as before mentioned this study has been commissioned by one of the most important Italian companies operating in the large scale retail sector), the WILMA (*Warehouse and Internal Logistics Management*) simulator is developed.

The objectives of the WILMA simulator are:

- to investigate the relationship between input parameters (*warehouse management* parameters) and output parameters (*warehouse performance* measures) for a correct warehouse design;
- to carry-out resources and costs analysis in function of different operative scenarios;
- to develop a high flexible simulation model (in terms of parameters variation and scenarios definition) adaptable to different systems without any large architecture changes.

4.3.1 The Warehouse Processes Modeling

The main modeling effort was carried out to recreate with satisfactory accuracy the most important operations of the real warehouse (i.e. trucks arrival and departure for items deliveries, forklifts and lift trucks for material handling operations, performance measures control and monitoring).

The simulation software adopted for the model implementation is the commercial package Anylogic™ by *XJ Technologies*.

Most of the logics and rules of the real warehouse are implemented by ad-hoc Java routines.

Figure 4.2 shows the simulation model Flow Chart while Figure 4.3 reports an example of Java code.

4.3.2 The Graphic User Interface for input/output parameters

The main variables of the WILMA simulation model have been completely parametrized in order to reproduce different warehouse operative scenarios. To this end the authors developed a dedicated Graphic User Interface (*GUI*) with a twofold functionality:

- to increase the simulation model flexibility changing its input parameters both at the beginning of the simulation run and at run-time observing the effect on the warehouse behavior (*Input Section*);
- to provide the user with all simulation outputs for evaluating and monitoring the warehouse performances (*Output Section*).

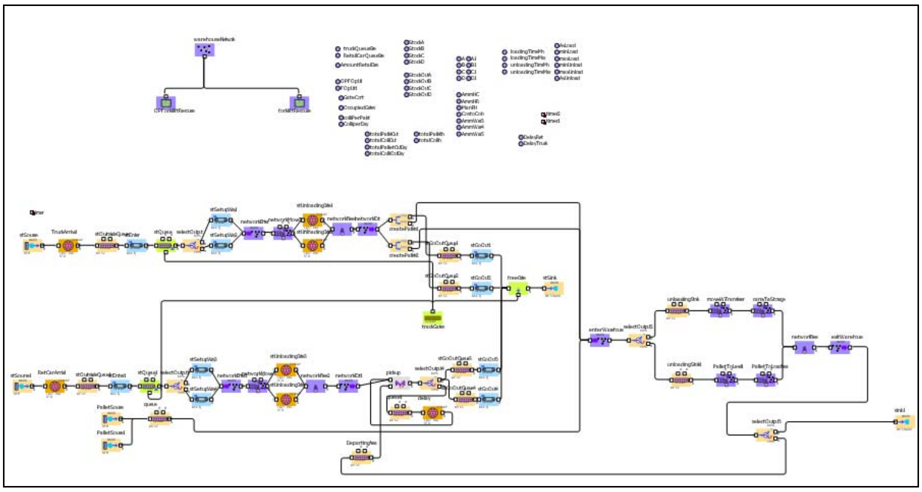


Figure 4.2 – The WILMA Simulation Model Flow Chart

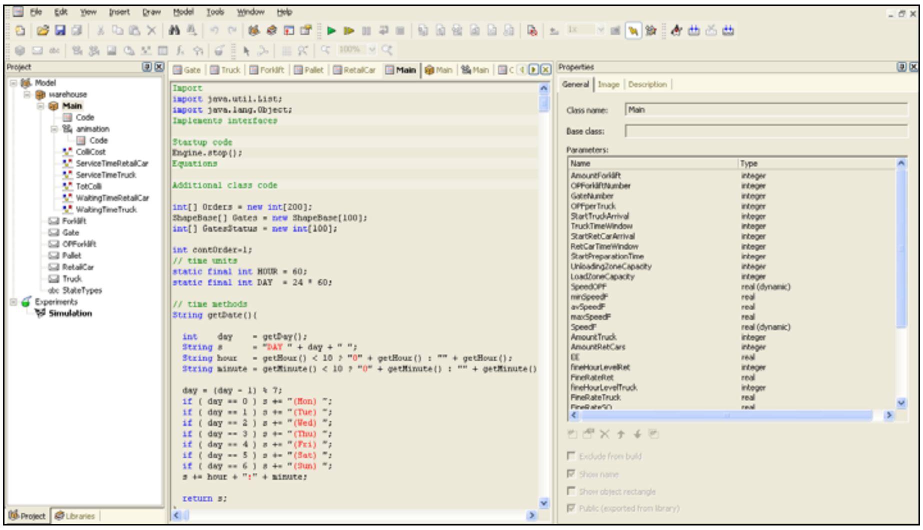


Figure 4.3 – An Example of Java code

The *Input Section* (Figure 4.4) can be subdivided in four different sub-sections:

- the *Suppliers' Trucks* section which contains the following parameters: suppliers' trucks arrival time, number of suppliers' trucks per day, time window in which suppliers' trucks deliver products;
- the *Retailers' Trucks* section which groups the following parameters: retailers' trucks arrival time, number of retailers' trucks per day, time window for retailers' trucks arrival, time for starting items preparation;
- the *Warehouse Management parameters* section in which the user can easily set the following parameters: shelves levels, number of forklifts, number of lift trucks, number of dock available for loading and unloading operations, forklifts and lift trucks efficiency, stock-out costs parameters;

- the *Logistics Internal Costs* section which contains the following parameters: fine cost for retailers/suppliers, time after which the warehouse has to pay fines to retailers, time after which suppliers have to pay fines to the warehouse.

Figure 4.4 – The GUI (Input Section)

The *Output Section* (Figure 4.5) provides the user with the simulation outputs for all the parameters necessary evaluating and monitoring the warehouse performances. These parameters are:

- forklifts utilization level;
- lift trucks utilization level;
- service level provided to suppliers' trucks;
- service level provided to retailers' trucks;
- waiting time of suppliers' trucks before starting the unloading operations;
- waiting time of retailers' trucks before starting the loading operations;
- number of packages handled per day (actual and average values);
- daily cost for each handled package (actual and average values).

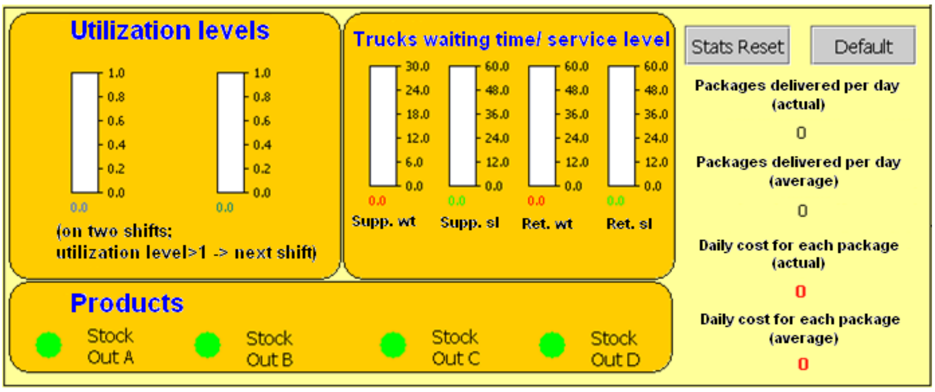


Figure 4.5 – The Output Section

4.4 Internal Logistics Management: scenarios definition and simulation experiments

The WILMA simulation model has been used to investigate the relationship between the most important *warehouse parameters* and *warehouse performance* measures for a correct design of the warehouse as well as to carry-out resources and costs analysis.

The main goal of the simulation study is to evaluate how different internal resources allocations affect some performance measures, i.e. the packages handled per day (actual and average), the daily cost for each handled package (actual and average) and the forklifts and lift trucks utilization level. More in detail, after a sensitivity analysis, the analytical relationship between the warehouse critical parameters and the performance measures is introduced.

4.4.1 Warehouse resources and costs analysis: design of simulation experiments

The input parameters (*factors*) taken into consideration are:

- the number of suppliers' trucks per day (*NTS*);
- the number of retailers' trucks per day (*NTR*);
- the number of forklifts (*NFT*);
- the number of lift trucks (*NMT*);
- the number of shelves levels (*SL*).

The variation of such parameters creates distinct operative scenarios characterized by different resources availability, allocation and utilization. The performance measures considered are:

- the average value of handled packages per day (*APDD*);
- the average value of the daily cost for each handled package (*ADCP*);
- the waiting time of suppliers' trucks before starting unloading operations (*STWT*);

- the waiting time of retailers' trucks before starting loading operations (*RTWT*).

The experiments planning is supported by the *Design of Experiments* (the *Full Factorial Experimental Design* is adopted because it is the most efficient way to study the joint effects of several factors). Table 4.I consists of factors and levels used for the design of experiments.

Factors	*Level 1*	*Level 2*
NTS	80	100
NTR	30	40
NFT	6	24
NMT	12	50
SL	3	5

Table 4.I – Factors and Levels of DOE

As shown in Table 4.I, each factor has two levels: in particular, Level 1 indicates the lowest value for the factor while Level 2 its greatest value. In order to test all the possible factors combinations, the total number of the simulation runs is 2^5. Each simulation run has been replicated three times, so the total number of replications is 96 (32x3=96). The simulation results have been studied, according to the various experiments, by means of the Analysis Of Variance (*ANOVA*) and of graphic tools.

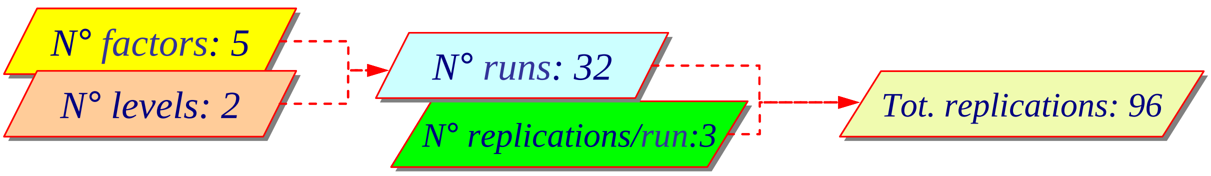


Figure 4.6 – The Full Factorial Experimental Design

4.5 Internal Logistics Management: simulation results analysis

Simulation results have been analyzed by means of *ANOVA* and graphic tools. The ANOVA partitions the total variability of the performance index in different components due to the influence of factors considered. According to Montgomery and Runger (2003), the total variability in the data, measured by the total corrected sum of squares SQ_T, can be partitioned into a sum of squares of differences between treatment (*factor level*) means and the grand mean (denoted as $SQ_{Treatments}$) and a sum of squares of differences related to observations within a treatment from the mean value of treatments (denoted as SQ_E), as reported in equation 4.1.

$$SQ_T = SQ_{Treatments} + SQ_E \qquad (4.1)$$

More in detail, the difference between observed treatment means and the grand mean defines differences between treatments, while observations differences within a treatment from the treatment mean can be due only to random errors. In this way, it is possible to understand which factors affect the performance measures, or, in other words, to introduce an analytical relationship (called *meta-model* of the simulation model) between each performance index and the factors being considered. Let Y_i be the i-th performance measure and let x_i be the factors, equation 4.2 expresses the i-th performance measure as linear function of the factors.

$$Y_i = \beta_0 + \sum_{i=1}^{5} \beta_i x_i + \sum_{i=1}^{5} \sum_{j>i}^{5} \beta_{ij} x_i x_j + \sum_{i=1}^{5} \sum_{j>i}^{5} \sum_{h>j}^{5} \beta_{ijh} x_i x_j x_h + \sum_{i=1}^{5} \sum_{j>i}^{5} \sum_{h>j}^{5} \sum_{k>h}^{5} \beta_{ijhk} x_i x_j x_h x_k + \\ + \sum_{i=1}^{5} \sum_{j>i}^{5} \sum_{h>j}^{5} \sum_{k>h}^{5} \sum_{p>k}^{5} \beta_{ijhkp} x_i x_j x_h x_k x_p + \varepsilon_{ijhkpn} \qquad (4.2)$$

where:

- β_0 is a constant parameter common to all treatments;
- $\sum_{i=1}^{5} \beta_i x_i$ are the five main effects of factors;
- $\sum_{i=1}^{5} \sum_{j>i}^{5} \beta_{ij} x_i x_j$ are the ten two-factors interactions;
- $\sum_{i=1}^{5} \sum_{j>i}^{5} \sum_{h>j}^{5} \beta_{ijh} x_i x_j x_h$ represents the three-factors interactions;
- $\sum_{i=1}^{5} \sum_{j>i}^{5} \sum_{h>j}^{5} \sum_{k>h}^{5} \beta_{ijhk} x_i x_j x_h x_k$ are the three four-factors interactions;
- $\sum_{i=1}^{5} \sum_{j>i}^{5} \sum_{h>j}^{5} \sum_{k>h}^{5} \sum_{p>k}^{5} \beta_{ijhkp} x_i x_j x_h x_k x_p$ is the sole five-factors interaction;
- ε_{ijhkpn} is the error term;
- n is the number of total observations.

In particular the analysis carried out aims at:

- identifying those factors that have a significant impact on the performance measures (*sensitivity analysis*);
- evaluating the coefficients of equation 4.2 in order to have an analytical relationship capable of expressing the performance measures as function of the most critical factors.

In the next Section, results analysis for the performance measures APDD, ADCP, STWT, RTWT is proposed.

4.5.1 Simulation results analysis for the number of handled packages per day (*APDD*)

Table 4.II reports the design matrix and the simulation results in terms of average number of handled packages per day.

The first five table columns show all the possible combinations of the factors levels while the last column reports the results provided by the WILMA simulation model for the APDD performance measure. Note that the APDD values reported in the last column of Table 4.II are values obtained as average on three simulation replications.

The Pareto Chart of the effects in Figure 4.7 allows to evaluate the predominant effects: in this case they are the first order effects and some effects of the second and third order.

According to the ANOVA theory, the non-negligible effects are characterized by *p-value* ≤ α where p is the probability to accept the negative hypothesis (the factor has no impact on the performance index) and α = 0.05 is the confidence level used in the analysis of variance. The most significant factors are:

- NTS (the number of suppliers' trucks per day);
- NTR (the number of retailers' trucks per day);
- NFT (the number of forklifts);
- NMT (the number of lift trucks);
- NTR*NMT (the interaction between the number of retailers' trucks per day and the number of lift trucks);
- NTS* NTR* NFT (the interaction between the number of suppliers' trucks per day, the number of retailers' trucks per day and the number of forklifts).

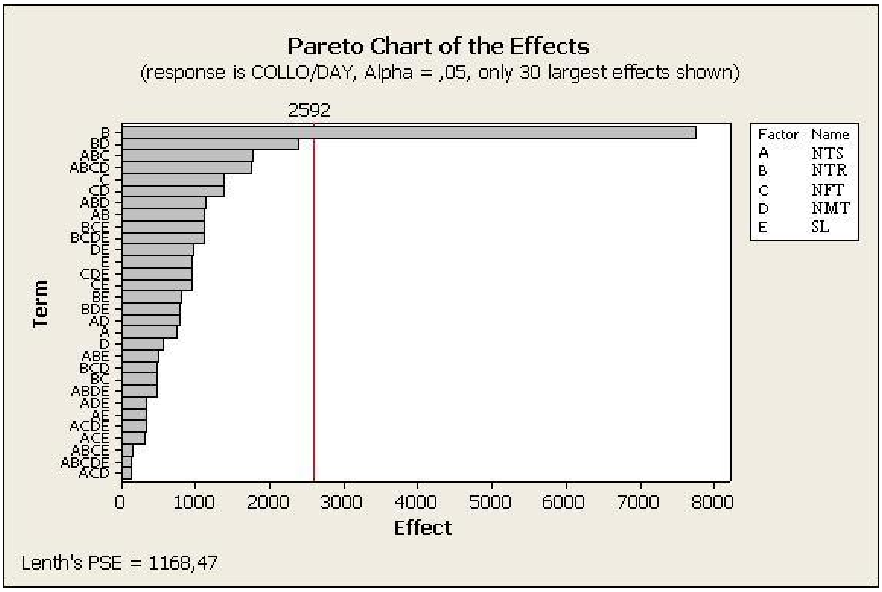


Figure 4.7 – The Pareto Chart for the APDD

NTS	*NTR*	*NFT*	*NMT*	*SL*	*APDD*
80	30	6	12	3	30370
80	30	6	12	5	30345
80	30	6	50	3	30439
80	30	6	50	5	30457
80	30	24	12	3	30421
80	30	24	12	5	30358
80	30	24	50	3	30387
80	30	24	50	5	30488
80	40	6	12	3	40574
80	40	6	12	5	40501
80	40	6	50	3	40603
80	40	6	50	5	40580
80	40	24	12	3	40551
80	40	24	12	5	40568
80	40	24	50	3	40553
80	40	24	50	5	40541
100	30	6	12	3	38528
100	30	6	12	5	37181
100	30	6	50	3	30361
100	30	6	50	5	30399
100	30	24	12	3	30388
100	30	24	12	5	30405
100	30	24	50	3	30416
100	30	24	50	5	30387,6
100	40	6	12	3	35846,1
100	40	6	12	5	37186,2
100	40	6	50	3	40498,8
100	40	6	50	5	40532,1
100	40	24	12	3	40550
100	40	24	12	5	35447,4
100	40	24	50	3	40530
100	40	24	50	5	40563,6

Table 4. II – Design Matrix and Simulation Results (APDD)

The ANOVA has been repeated for the most important factors and the results are reported in Table 4.III:

- the first column reports the sources of variations;
- the second column is the degree of freedom (*DOF*);
- the third column is the Adjusted Sum of Squares;
- the 4th column is the Adjusted Mean Squares;

- the 5th column is the *Fisher* statistic;
- the 6th column is the *p-value*.

Source	***DF***	***AdjSS (10^{-7})***	***AdjMS (10^{-7})***	***F***	***P***
Main Effects	4	50,30	125,75	23,22	0
2-Way interactions	1	45,24	4,52	8,35	0
3-Way interactions	1	24,84	2,48	4,59	0,04
Residual Error	25	13,53	0,54		
Total	31				

Table 4.III – ANOVA Results for the APDD (most significant factors)

Results confirm that those factors affecting the APDD have a p-value lower than the confidence level adopted α = 0.05. The input-output meta-model for the APDD is the following:

$$APDD = 21777 + 21{,}46 * NTS + 348{,}74 * NTR - 167{,}083 * NFT + \\ - 423{,}71 * NMT + 12{,}51 * (NTR * NMT) + 0{,}028 * (NTS * NTR * NFT) \quad (4.3)$$

Equation 4.3 is the most important result of the analysis: it is a powerful tool that can be used for correctly defining, in this case, the average number of packages handled per day in function of the warehouse available resources.

4.5.2 Simulation results analysis for the average daily cost per handled package (*ADCP*)

The same analysis has been carried out taking into consideration the average daily cost per handled packages (*ADCP*). Table 4.IV reports the design matrix and the simulation results. The normal probability plot in Figure 4.8 allows to evaluate the predominant effects (red squares): in this case they are the first order effects and some effects of the second order:

- NTR (the number of retailers' trucks per day);
- NMT (the number of lift trucks);
- SL (the number of shelves levels);
- NTR*SL (the interaction between the number of retailers' trucks per day and the number of shelves levels);
- NFT*SL (the interaction between the number of forklifts and the number of shelves levels).

Figure 4.9 shows the trend of ADCP in function of the main effects:

- NTR;
- NMT;
- SL.

As reported in Figure 4.9, when the number of lift trucks increases, the average daily cost for packages delivered decreases; the contrary happens with the shelves levels and the number of retailers' trucks variations. Finally, Figure 4.10 presents the plots concerning the interaction effects between some couples of parameters (i.e NTR-NFT, NFT-SL).

The results obtained by means of DOE and ANOVA allow to correctly allocate warehouse internal resources in order to maximize the average number of handled packages per day and to minimize the total logistics internal costs. In effect an accurate combination of the number of forklifts and lift trucks, help to keep under control these performance measures. The validity of the results, obtained thanks to ANOVA, is still confirmed by residuals analysis. The starting hypothesis which ensure the validity of the ANOVA (observations normally and independently distributed, observations with the same variance for each possible combination of the factors levels) have been verified by using Normal Probability plots, residuals versus the order of the fitted data plots, and histograms of the residuals.

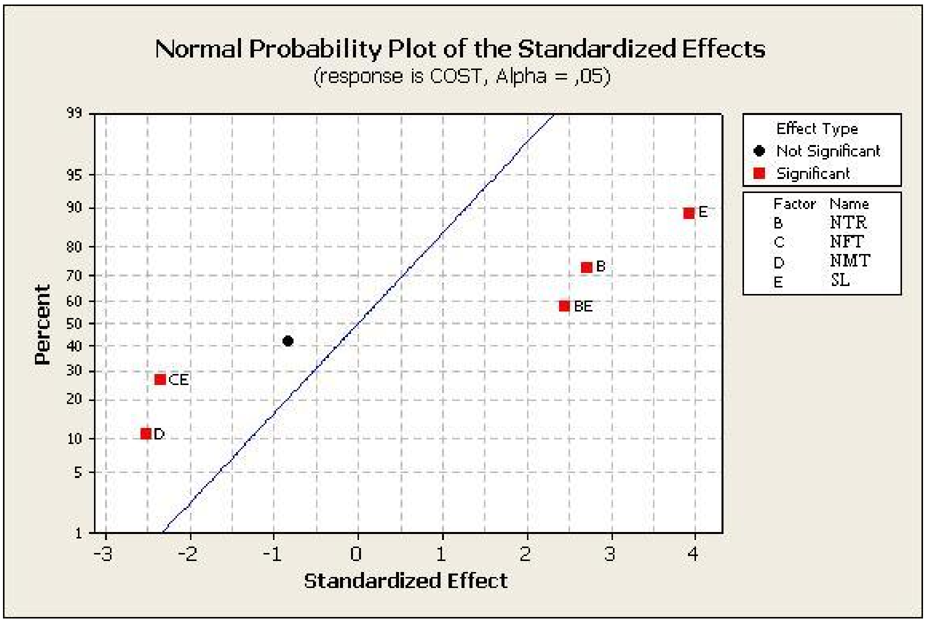


Figure 4.8 – The Most Significant Effects for the ADCP

NTS	*NTR*	*NFT*	*NMT*	*SL*	*ADCP*
80	30	6	12	3	1,38
80	30	6	12	5	1,33
80	30	6	50	3	0,48
80	30	6	50	5	0,483
80	30	24	12	3	3,06
80	30	24	12	5	3,91
80	30	24	50	3	2,27
80	30	24	50	5	0,623
80	40	6	12	3	1,38
80	40	6	12	5	13,82
80	40	6	50	3	0,45
80	40	6	50	5	11,54
80	40	24	12	3	4,69
80	40	24	12	5	5,3
80	40	24	50	3	3,69
80	40	24	50	5	2,89
100	30	6	12	3	3,05
100	30	6	12	5	4,31
100	30	6	50	3	0,53
100	30	6	50	5	6,72
100	30	24	12	3	5
100	30	24	12	5	6,28
100	30	24	50	3	0,64
100	30	24	50	5	0,62
100	40	6	12	3	3,72
100	40	6	12	5	8,18
100	40	6	50	3	1,06
100	40	6	50	5	8,97
100	40	24	12	3	2,7
100	40	24	12	5	11
100	40	24	50	3	0,48
100	40	24	50	5	0,47

Table 4.IV – Design Matrix and Simulation Results (ADCP)

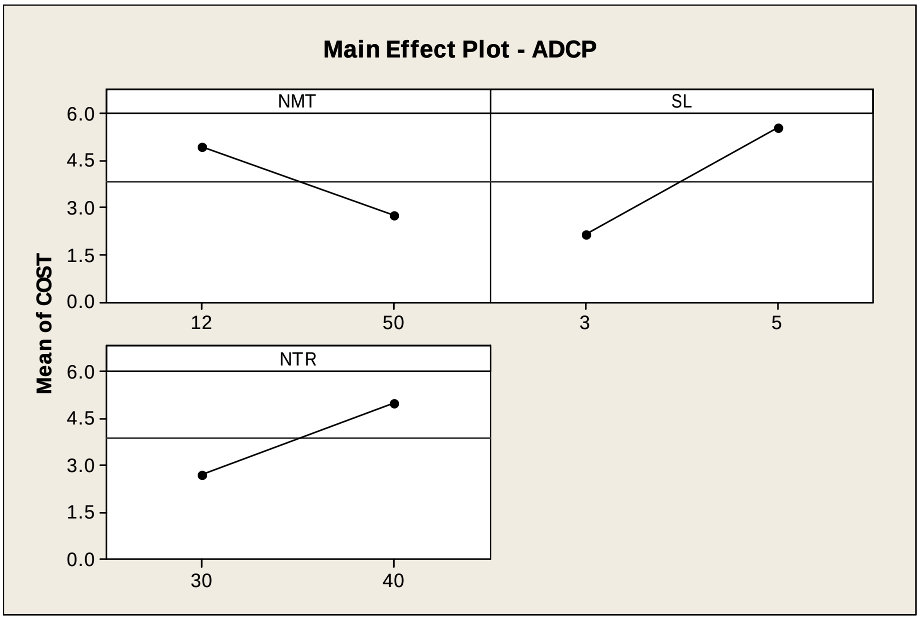


Figure 4.9 – ADCP versus Main Effects

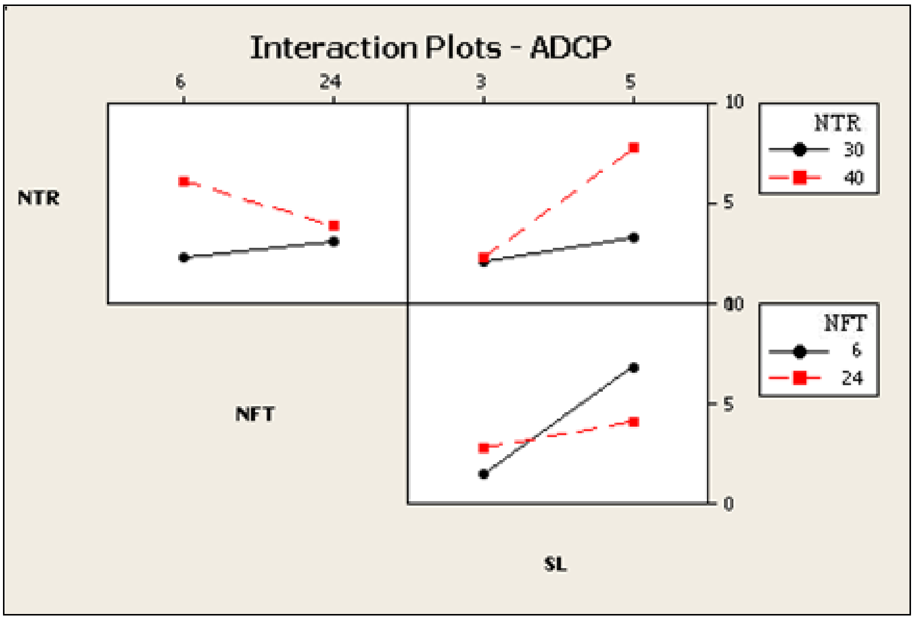


Figure 4.10 – Interactions Plots for the ADCP

4.5.3 Simulation results analysis for the waiting time of suppliers' trucks before starting the unloading operation (*STWT*)

This Section focuses on evaluating the analytical relationship between factors reported in Table 4.IV (the number of suppliers' and retailers' trucks per day, the number of forklifts and lift trucks, the number of shelves levels) and the waiting time of suppliers' trucks before starting the unloading operation and the waiting time of retailers' trucks before starting the loading operation. Such relationships should be used for a correct system design and management.

The first analysis carried out aims at detecting factors that influence the waiting time of suppliers' trucks before starting the unloading operations (*STWT*). Adopting also in this case a confidence level $\alpha = 0.05$, the Pareto Chart in Figure 4.11 highlights factors that influence the response parameter STWT. These factors are:

- the number of retailers' trucks per day (*NTR*);
- the number of shelves levels (*SL*);
- the interaction factor between NTR and SL (*NTR*SL*).

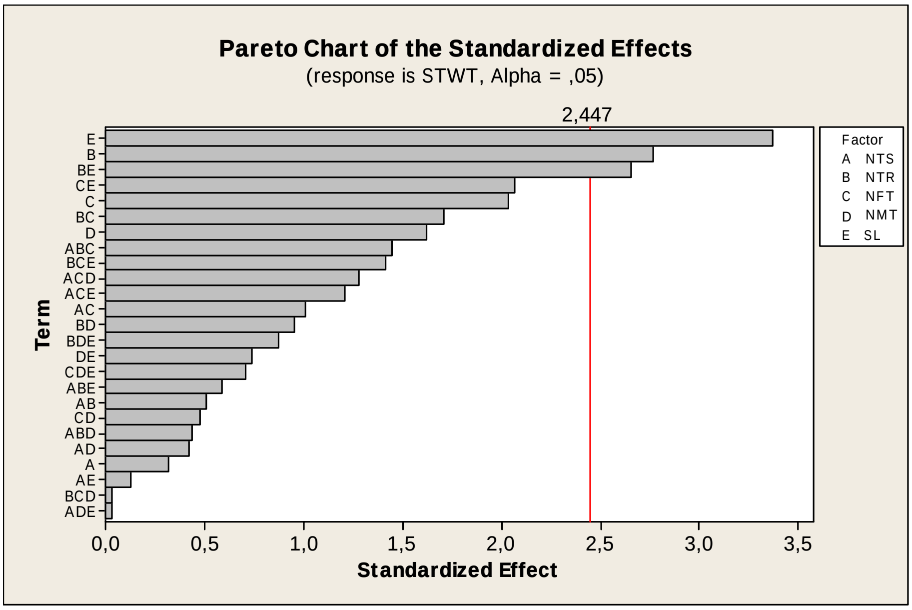


Figure 4.11 – The Pareto Chart for the STWT

Repeating the ANOVA for the most important factors, it is confirmed that factors are correctly chosen because their *p-value* is lower than the confidence level adopted, as reported in Table 4.V.

Source	***DF***	***AdjSS (10^4)***	***AdjMS (10^4)***	***F***	***P***
Main Effects	2	14,38	7,19	8,26	0,00 2
2-Way interactions	1	5,34	5,34	6,14	0,02
Residual Error	28	24,39	0,871		
Total	31				

Table 4.V – ANOVA Results for Significant Factors

The input-output meta-model which expresses the analytical relation between the STWT parameter and the most significant factors is reported in equation 4.4:

$$STWT = 713,58 - 24,19 * NTR - 234,32 * SL + \\ + 8,17 * (NTR * SL) \tag{4.4}$$

This equation can be adopted for correctly explaining how the waiting time of suppliers' trucks before starting the unloading operation changes in function of the system available resources.

4.5.4 Simulation results analysis for the waiting time of retailers' trucks before starting loading operations (*RTWT*)

The same analysis has been carried out taking into consideration the waiting time of retailers' trucks before starting loading operations (*RTWT*).

Figure 4.12 shows the Normal Probability Plot of the Standardized Effects in which the predominant effects can be distinguished; in this case they are the first order effects and some effects of the second and third order:

- the number of retailers' trucks per day (*NTR*);
- the number of lift trucks (*NMT*);
- the number of shelves levels (*SL*);
- the interaction factor between NTS and NTR (*NTS*NTR*);
- the interaction factor between NTS and NFT (*NTS*NFT*);
- the interaction factor between NTR and SL (*NTR*SL*);
- the interaction factor between NFT and NMT (*NFT*NMT*);
- the interaction factor between NFT and SL (*NFT*SL*);
- the interaction factor between NTR, NFT and SL (*NTR*NFT*SL*);
- the interaction factor between NFT, NMT and SL (*NFT*NMT*SL*).

Table 4.VI reports the *p-value* for the predominant effects while equation 4.5 describes the analytical relation between the RTWT and the predominant effects:

$$RTWT = 261,843 - 13,125 * NTR + 3,159 * NMT - 166,299 * SL + 0,081 * (NTS * NTR) + \\ - 0,029 * (NTS * NFT) + 5,930 * (NTR * SL) + 0,122 * (NFT * NMT) + 1,027 * (NFT * SL) + \\ - 0,073 * (NTR * NFT * SL) - 0,022 * (NFT * NMT * SL) \tag{4.5}$$

Figure 4.13 plots equation 4.5 in terms of main effects: each plot provides additional information about the effects of the most significant factors on the RTWT.

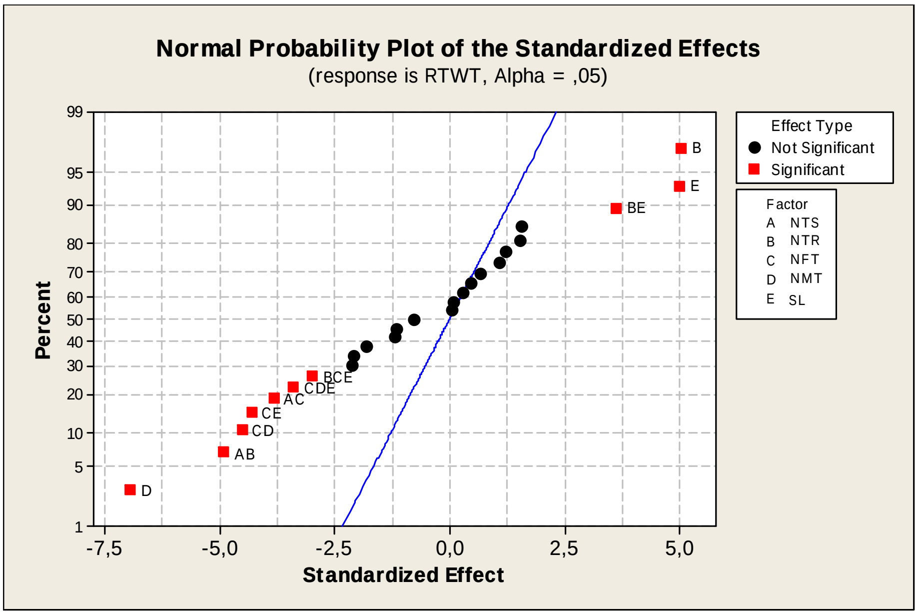


Figure 4.12 – The Normal Probability Plot for the RTWT

Considering the NTR parameter, if the number of retailers' trucks per day increases the waiting time of retailers' trucks before starting the loading operations (*RTWT*) increases too because of trucks' traffic density. The same happens if the number of shelves levels (*SL*) changes from 3 to 5; on the other hand, when increasing the number of lift trucks (*NMT*) from its low to high value, the RTWT significantly decreases.

Source	***DF***	***AdjSS (10^4)***	***AdjMS (10^4)***	***F***	***P***
Main Effects	5	39,65	7,93	20,32	0,001
2-Way interactions	10	39,46	3,94	10,11	0,005
3-Way interactions	10	11,96	1,19	3,07	0,045
Residual Error	6	23,41	0,39		
Total	31				

Table 4.VI – ANOVA Results for the most significant factors

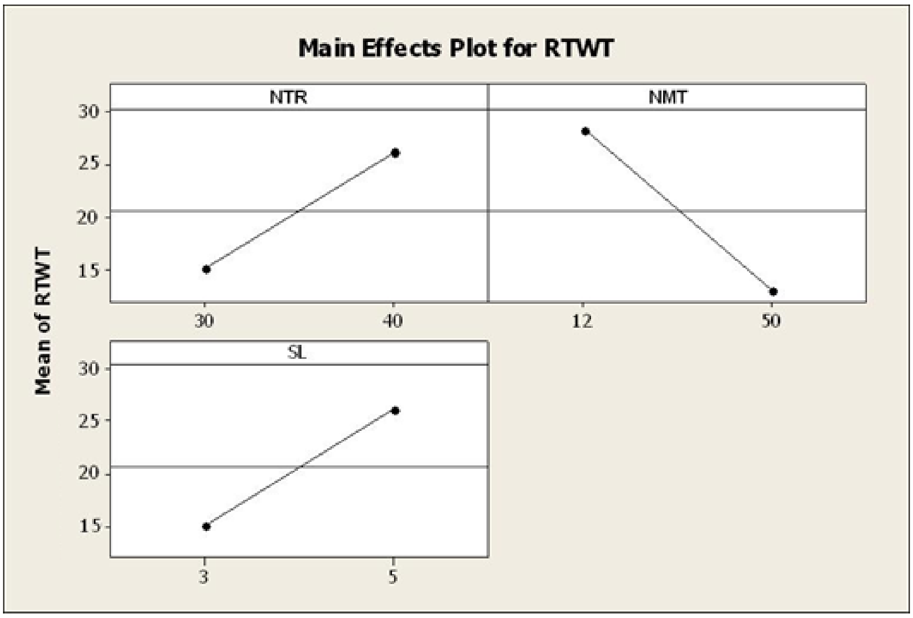


Figure 4.13 – Main Effects Plots for RTWT

Figure 4.14 shows simulation results for the RTWT parameter projected on a cube considering the NTR, NMT and SL parameters. At each corner of the cube the RTWT values are reported: setting NMT at its high value while NTR and SL at their low values is the best choice to obtain the lowest RTWT value.

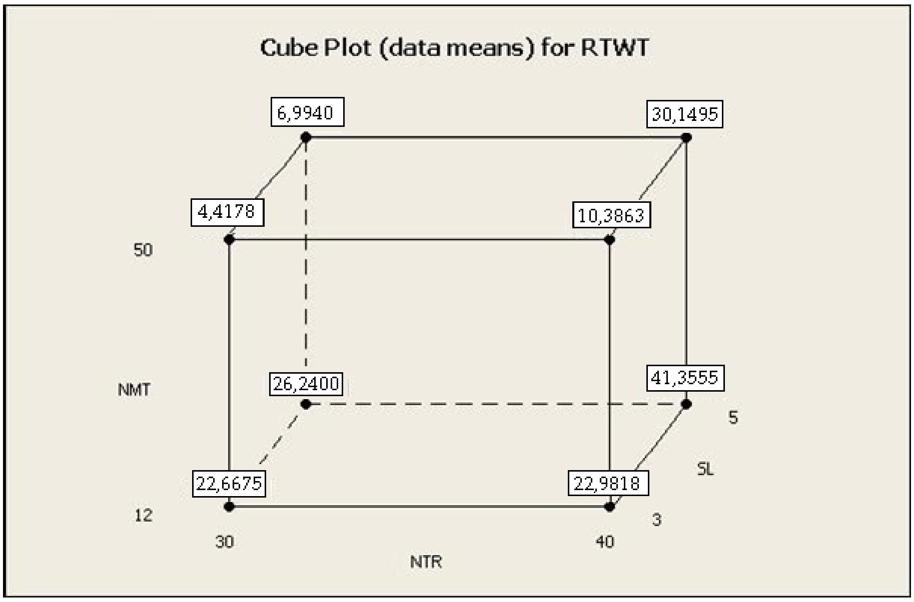


Figure 4.14 – Cube Plot for RTWT

Moreover, Figure 4.15 reports the three-dimensional surfaces of the response parameter in function of different combinations of the input parameters.

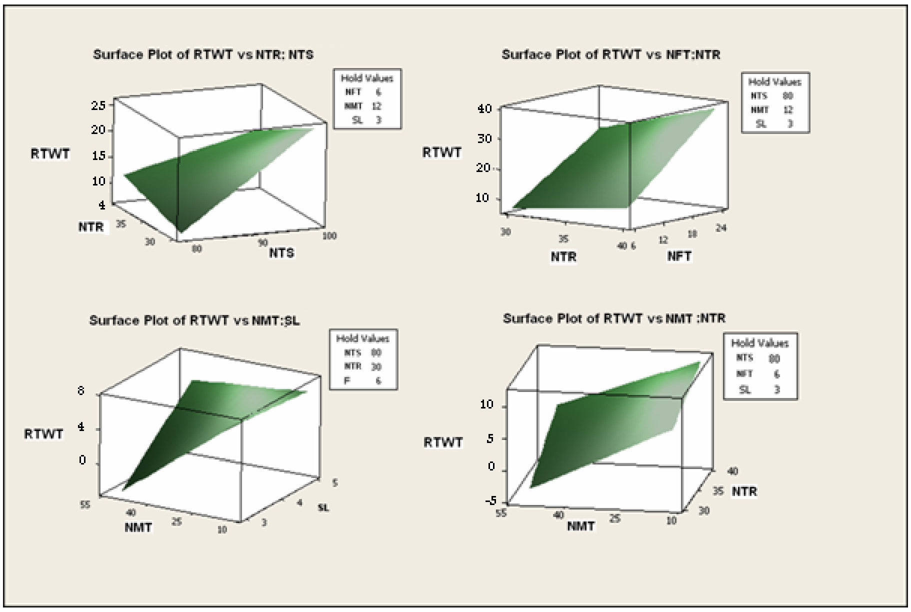


Figure 4.15 – Response Surfaces for RTWT

4.6 Conclusions

After an introduction on the role of warehouses in the logistic systems, the WILMA simulation model of a real warehouse supporting the large scale retail sector is presented. Then two case studies are described.

The first analysis deals with the internal logistics management problem within the warehouse in order to evaluate how different internal resources allocation affect some performance measure, i.e. the average value of handled packages per day, the average daily cost for each handled package.

The second case study focuses on evaluating the analytical relationship between some input parameters (i.e. the number of suppliers' and retailers' trucks per day, the number of forklifts and lift trucks, the number of shelves levels) and the output performance measures (the waiting time of suppliers' trucks before starting the unloading operation and the waiting time of retailers' trucks before starting the loading operation) in order to introduce analytical relationships for a correct warehouse design and management.

References

Anthony, R.N., 1965. Planning and control systems: a framework for analysis. Harvard University Graduate School of Business Administration, Boston.

Ashayeri, J., Gelders, L.F., 1985. Warehouse design optimization. *Operational Research*, 21, 285-294.

Bloomberg, D., LeMay, S., Hanna, J., 2002. Logistics. Upper Saddle River: Prentice Hall.

Brynzer, H., Johansson, M.I., 1995. Design and performance of kitting and order picking systems. *Production Economics*, 41, 115-125.

Coyle, J., Bardi, E., Langley, C., 2003. The management of business Logistic: a supply chain perspective. Mason.

De Koster, R., Le-Duc, T., Roodbergen, K., 2007. Design and control of warehouse order picking: a literature review. *Operational Research*, 182, 481-501.

Frazelle, E.H, Hackman, S.T., Passy, U., Platzman, L.K., 1994. The forward-reverse problem. *Optimization in Industry*, 2, 43-61.

Graves, S.C., Hausman, W.H., Schwarz, L.B., 1977. Storage retrieval interleaving in automatic warehousing systems. *Management Science*, 23 (9), 935-945.

Gudehus, T., 1973. Principles of order picking: operations in distribution and warehousing systems. Girardet.

Hausman, W.H., Schwarz, L.B., Graves, S.C., 1976. Optimal storage assignment in automatic warehousing systems. *Management Science*, 22 (6), 629-638.

Hariga, M.A., Jackson, P.L., 1996. The warehouse scheduling problem: formulation and algorithms. *IIE Transactions*, 28 (2), 115-127.

Lambert, D.J., Cooper, M.C., Pagh, J.D., 1998. Supply chain management, implementation issues and research opportunities. *Logistics Management*, 9 (2), 1-19.

Montgomery, D.C., Runger, G.C., 2003. Applied statistics and probability for engineers. McGraw-Hill, London.

Schwarz, L.B., Graves, S.C., Hausman, W.H., 1978. Scheduling policies for automatic warehousing systems: simulation results. *AIIE Transactions*, 10 (3), 260-270.

Van den Berg, J.P., 1999. A literature survey on planning and control of warehousing systems. *IIE Transactions*, 31, 751-762.

Van Oudheusden, D.L., Tzen, Y, Ko, H.T., 1988. Improving storage and order picking in a person-on-board AS/R system. *Engineering Costs and Production Economics*, 13, 273-283.

Acknowledgements

This thesis is the result of sacrifices, hard work and dedication with characterized the three years PhD course at the Mechanical Department of the University of Calabria (Italy), Industrial Engineering Section.

It would not have been possible without support and constructive feedback from a number of people.

First of all, I would like to take this opportunity to give thanks and show gratitude to the Industrial Engineering team. In particular, I would like to give thanks to Prof. Enrico Papoff for his guidance and for sharing his knowledge; to Prof. Giovanni Mirabelli for his rigour, expertise, care and helpfulness showed not only professionally but also humanly, and for always making himself available to answer countless questions; to Dr. Francesco Longo for his patience, helpfulness, friendship, for sharing his strong experience giving me the chance to attend the most important International conferences and meetings on Modeling & Simulation, and for his precious suggestions on how to structure this thesis; to my colleague Antonio Cimino for his friendship and seriousness; to my colleague and roommate Sabrina Rondinelli for her friendship and moral support.

I would also like to express my gratitude to Prof. Agostino Bruzzone, full professor at University of Genoa, Savona Campus, Italy.

In addition, my appreciation goes to my opponent, Prof. Luigino Filice, for his constructive criticism in finalizing this thesis.

Finally, my gratitude goes to my friends for their affection and constant support and to all the people I have met during these three years.