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Supply Chain Management Based on Modeling & Simulation: State of the Art and Application Examples in Inventory and Warehouse Management

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1. Introduction

The business globalization has transformed the modern companies from independent entities to extended enterprises that strongly cooperate with all supply chain actors. Nowadays supply chains involve multiple actors, multiple flows of items, information and finances. Each supply chain node has its own customers, suppliers and inventory management strategies, demand arrival process and demand forecast methods, items mixture and dedicated internal resources. In this context, each supply chain manager aims to reach the key objective of an efficient supply chain: 'the right quantity at the right time and in the right place'.

To this end, each supply chain node (suppliers, manufacturers, distribution centers, warehouses, stores, etc.) carries out various processes and activities for guarantying goods and services to final customers. The competitiveness of each supply chain actor depends by its capability to activate and manage change processes, in correspondence of optimistic and pessimistic scenarios, to quickly capitalize the chances given by market. Such capability is a critical issue for improving the performance of the 'extended enterprise' and it must take into account the complex interactions among the various supply chain nodes. The evaluation of correct trades-offs between conflicting factors, such as inventory reduction and fill rates, customers' satisfaction and transportation cost, sales loss and inventory costs, resources management and internal costs, are (among others) the most important tasks of a competent supply chain manager.

Therefore, supply chains have to be regarded as complex systems; a wide range of factors usually affects the behaviour of complex systems. The ways in which such factors interact and the stochastic nature of their evolution over the time increase the complexity of many real-world supply chains up to critical levels, where the use of ad-hoc methodologies, techniques, applications and tools is the only way to tackle problems and succeed in identifying proper and optimal solutions (Castilla and Longo, 2010).

To this end, Modelling & Simulation (M&S) has been widely recognised as the best and most suitable methodology for investigation and problem-solving in real-world complex systems in order to choose correctly, understand why, explore possibilities, diagnose problems, find optimal solutions, train personnel and managers, and transfer R&D results to real systems (Banks, 1998). In addition, M&S, regardless of the application domain, usually provides innovative solutions and new user-friendly tools, with special attention to integration into business processes and management. The identification of proper and optimal solutions in complex real-world systems often requires the solution of multi-objective problems involving multiple stochastic variables. As stated in Chen (2003), real world optimisation problems involve contrasting and competing objectives and require the definition of multiple performance measures. In such a context, where the whole is greater than the sum of parts, successful approaches require something more than simple mathematical or stochastic models. M&S capabilities to recreate (with high level of accuracy) the intrinsic complexity of real-world systems allows to find out and test alternative solutions under multiple constraints and to monitor, at the same time, multiple performance measures.

In this chapter the use of M&S as enabling technology is investigated, highlighting the contribution of this approach in supply chain management (with a specific focus on supply chain inventory and warehouse management). The objective of this chapter is twofold:

• provide the reader with a survey of most recent research works including theories and M&S based methodologies for supply chain inventory and warehouse management;

• propose two application examples (based on real case studies) that respectively consider the supply chain inventory management and the supply chain warehouse management. The application examples deal with advanced modeling approaches and simulation models for investigating the inventory management problem along the supply chain and warehouse management problem within a single supply chain node. In both the application examples, the simulators are decision-making tools capable of analyzing different scenarios by using approaches based on multiple performance measures and user-defined set of input parameters. The first application example considers the entire supply chain and it is mainly devoted to investigate the behaviour (in terms technical efficiency, i.e. fill rates, on hand inventory, etc.) of different inventory control policies. The second application example deals with a single supply chain node (a distribution center) and considers the effect of resources management on internal logistic costs.

Before getting in the details of the study, in the sequel a brief summary of the chapter is reported. Section 2 structures the state of the art on the most relevant articles in the field of supply chain inventory and warehouse management (also highlighting critical issues in supply chain Modeling & Simulation). The remainder of the chapter is structured in two different parts. Sections 3 and 4 propose the first application example: a supply chain conceptual and four different inventory control policies are presented and discussed; the supply chain conceptual model is then translated into a computerized simulation model (by using an advanced modelling approach) and the inventory management problem along the supply chain is investigated. Sections 5 deals with the second application example: a simulation model is presented and used for investigating interactions among operational strategies, available resources and internal logistics costs in a real warehouse. Finally section 6 summarizes conclusions and lessons learned.

2. Supply Chains: a state of the art overview on inventory and warehouse management

A Supply Chain is a network of different entities or nodes (suppliers, manufacturers, distribution centers, warehouses, stores, etc.) that provide materials, transform them in intermediate or finished products and deliver them to customers to satisfy market requests. Among others two main factors characterize a supply chain node: the demand and 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 characterised by a great number of critical issues: market needs (volumes and production ranges), industrial processes (machines downtimes, transportation modes) and supplies (parts quality, delivery schedules). The market demand and the productive capacity also generate a flow of items and finances towards and from the supply chain nodes. Needless to say, the supply chain management takes care of the above-mentioned issues, studying and optimising the flow of materials, information and finances along the entire supply chain. The main goal of a supply chain manager is to guarantee the correct flows of goods and information throughout the supply chain nodes for assuring the right goods in the right place and at the right time.

Among others, the inventory management problem along the supply chain plays a critical role because it strongly affects the supply chain performances. Lee and Billington (1993) consider the inventory control as the only tool to protect supply chain stability and robustness. Longo and Ören (2008) also assert that an efficient inventory management along the supply chain positively affects the supply chain resilience. In effect, the objective of the supply chain inventory management is to satisfy the ultimate customer's demand increasing the quality and service level and decreasing at the same time total costs. Inventories affect supply chain costs and performances 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 the finished products because they can be easily adopted for different production processes;
- levels of responsiveness, e.g., products delivery could be made without strict lead times whereas raw materials transformation usually requires stringent lead times.

However, the inventory problem is not the only critical issue affecting the supply chain performances. In effect, the internal logistics management within each supply chain node (i.e. warehouse management in a distribution center) similarly affects supply chain performances. The correct organisation of all the logistic processes and activities that take place within a supply chain node (i.e., capability of using material-handling systems efficiently, time windows planning for suppliers/retailers unloading/loading operations, etc.) could have a remarkable impact on both processes upstream and downstream the supply chain and on supply chain node internal costs.

This section surveys the most relevant articles both in the field of supply chain inventory management and in the field of internal logistics management (with a specific focus on warehouse management). Section 2.1 and section 2.2 are respectively dedicated to the inventory management problem along the supply chain and to the internal logistics management. In addition, section 2.3 discusses some critical issues in supply chain Modeling & Simulation.

2.1 The supply chain inventory management problem: a survey

The inventory management system at each supply chain node has to answer to three different questions: (i) how often to review the stock status; (ii) when to order new products; (iii) quantity of new products. In order to help supply chain managers and practitioners to approach and face the supply chain inventory management problem and answer to the previous questions, this section surveys the most relevant studies in the supply chain inventory management area. The survey also emphasizes the potentials of the M&S approach as enabling technology for supply chain inventory management.

A general survey on supply chain inventory simulation can be found in Cimino et al. (2010). Specific studies on the base stock policy are reported in Roundy and Muckstadt (2000), Graves (1999) and Parker and Kapuscinski (2004). In the first case the authors propose an heuristic computation of the base stock policy parameters obtaining a good approximation to the optimal policy. In the second case, the base stock policy is applied in correspondence of different operative scenarios (demand pattern variation). In the third case the authors demonstrate that the base stock policy, in a two echelon supply chain, obtains the best performance (respect to the other inventory policies) if downstream stages capacity is lower than upstream ones.

Similar studies have been carried out for other inventory control policies. The influence (on supply chain performances) of the most applied inventory policies (economic order quantity with stationary demand and dynamic economic lot-size with non stationary demand) is reported in Zipkin (2000). Interesting approaches to the supply chain inventory management problem can also be found in the following books: Simchi-Levi (2000), Stadtler and Kilger (2000) and Chopra and Meindl (2001).

As mentioned earlier, nowadays the supply chain manager has to take into account the concept of extended enterprise. Useful managerial insights must come from a research effort devoted to consider the inventory management problem along the entire supply chain. In effect, many authors provide an enlarged framework for inventory systems analysis. Wikner *et al*. (1991) face the inventory management problem along the supply chain considering as critical the tuning of order policy parameters, the reduction of delivery delays in each stage of the supply chain, the distribution echelon elimination and the enhancement of decisions rules and information flow (the latter by separating customers' real orders from the orders emitted for the safety stock). The authors propose a model composed by a single production plant, various distribution centres and retailers, each one operating under specific inventory control policies. Simulation is used for evaluating the best inventory policies that minimizes demand fluctuation along supply chain.

As matter of fact, enlarged inventory management scenarios (focused on entire supply chains instead of a single stage inventory problem) usually require the use of Modeling & Simulation. Lee et al. (2002) underline the need to use M&S not only for inventory management problems but as support tool for analyzing and designing the whole supply chain. Existing analytical methods are not able to handle all the dynamically changing supply chain variables; a M&S based approach is a powerful tool for managing the stochastic behavior of supply chains. A complete list of advantages and disadvantages in using simulation approach for supply chain modeling can be found in Ingalls (1998).

In effect different studies are reported in literature regarding the use of M&S not only for supporting supply chain inventory management. F.T.S. Chan and H.K. Chan (2005) use simulation for supply chain design by building and testing five different supply chain models. Supply chain performances are calculated following a multi measures based

approach. Persson and Olhager (2002) propose a supply chain design problem based on a real case study; the authors evaluate alternative supply chain scenarios with the aim of improving quality and costs and understanding how these parameters affect each other (as in the previous case, a multi measures based approach to supply chain performance is propsoed). Zhang and Zhang (2007) deal with the information sharing implementation problem in a multi stage supply chain. They use simulation for analyzing the impact of information sharing on supply chain performances.

Many of the research studies based on Modeling & Simulation approaches (not only those studies focusing on supply chain inventory management) highlight that a multi measures based approach is required for obtaining successful results (Thor, 1994). Viswanadham (1999) states that supply chain performance measures can be divided in two categories: quantitative (such as fill rates, costs, inventory levels, resources utilization) and qualitative (such as customer satisfaction, products quality, supply chain vulnerability, supply chain resilience). A complete description of quantitative and qualitative measures is reported in F.T.S. Chan and H.K. Chan (2005), whilst a comprehensive analysis of the most recent qualitative performance measures, including supply chain resilience and vulnerability, can be found in Bruzzone et al. (2006), Longo and Oren (2008). Baganha and Cohen (1998) provide different criteria for choosing new supply chain performance measures. Moreover, an accurate overview of supply chain performance measures can be found in Beamon (1998, 1999).

The use of simulation tools supports the evaluation of multiple performance measures under the effects of different constraints and combinations of critical parameters such as inventory control policies, lead times, demand intensity, demand variability, etc. Specific examples regard supply chain inventory management problems. Axsater (2003) considers the problem of minimizing the holding cost under fill rate constraints; the approach proposed by the author allows the evaluation of the optimal inventory control policy. Moinzadeh (2002) studies the effects of information sharing on the inventory management problem within a two echelons supply chain; the author proposes an inventory control policy (for suppliers) that takes into consideration the stores inventory position and compares such policy to those policies not using this information. A simulation study for understanding the impact of inaccurate inventory information on supply chain performance is presented by Fleisch and Tellkamp (2005); once again, a multi measures approach, considering costs and stock outs, is proposed.

An interesting approach in studying the effects of inventory control policies on supply chain performance is proposed by Tagaros and Vlachos (2001). They consider a periodic-review inventory control policy working with two replenishment modes (regular and emergency). The paper demonstrates that such control policy works better (in terms of costs) than a traditional one. Cost minimization is obtained with heuristic algorithms able to find near optimal solutions if compared with optimal solutions derived by simulation. Graves and Willems (2005) propose a more centric approach on the entire supply chain. They deal with supply chain configurations in terms of suppliers, parts, processes and transportation modes to be selected at each stage trying to minimize the total supply chain cost. Another study on the whole supply chain using modeling and simulation is presented by Ganeshan et al. (2001). The authors study the impact of critical inventory parameters and management techniques on the performance of an expanded and comprehensive supply chain. Particular attention is also devoted to the inventory management problem along the supply chain in the case of reverse logistics. An updated survey of the state of the art on inventory with products returns can be found in Cimino et al. (2010).

The study of inventory systems in real stochastic supply chains is one of the major concerns in today's supply chain management. As soon as the number of parameters affecting supply chain performances becomes high and the objective becomes the whole supply chain analysis, simulation plays a more critical role in finding the optimal trade off among the involved variables, i.e. inventory policies, transportation cost, lead times, demand patterns, customers' satisfaction (Chang and Makatsoris, 2001). To this end Modelling & Simulation based approaches are jointly used with advanced statistics techniques such as Design of Experiment, DOE, and Analysis of Variance, ANOVA, (Suwanruji and Enns, 2006; Curcio and Longo, 2009).

The literature survey highlights that:

- simulation combined with statistic techniques is usually used for analyzing supply chain scenarios (different combinations of critical parameters);
- there is a lack in the research studies on inventory systems of real multi-echelon stochastic supply chain, considering a complete set of operative scenarios regarding customers' demand intensity, customers' demand variability, lead times and the impact of such scenarios on multiple performance measures. In such a context, research works based on analytical approaches are characterized by simplifying assumptions, studies based on Modelling & Simulation consider a limited number of operative scenarios, or a limited number of inventory policies, or they are based on theoretical case study or, at last, they consider only one performance measure.

Therefore the main contribution of the first application example proposed in this chapter is a focus on a real three-echelon stochastic supply chain; a supply chain simulation model is used for investigating a comprehensive set of operative scenarios including different inventory control policies under customers' demand intensity, customers' demand variability and lead times constraints.

As additional aspect (keeping in mind the literature overview proposed above), it is worth say that a supply chain manager needs of decision-making tools capable of investigating the effects of critical parameters on multiple performance measures. Note that different supply chains are characterized by different critical parameters, therefore a simulation based decision-making tool should provide to managers (i) high flexibility in terms of scenarios definition and (ii) critical parameters and performance measures selection.

2.2 Internal logistics: a survey on warehouse management

As for the inventory problems, Simulation can be also profitably used for supply chain node design and management, regardless of the node type (i.e. Bruzzone et al., 2007 and Longo, 2010 respectively propose the use of simulation for logistics node design and for integrating security activities in the normal operations of a container terminal part of an extended supply chain). It is worth saying that the internal logistics management of each supply chain node (above all from the warehouse management point of view) also provides to researchers and practitioners challenging problems.

Warehouses are usually large plain buildings used by exporters, importers, wholesalers, manufacturers for goods storage. Warehouses are equipped with loading docks, cranes, forklifts and material handling systems for moving goods. The main processes that take place within a warehouse are receiving items, storage, retrieval, picking, shipping. Warehousing costs can be distinguished in general overhead costs, delivery costs and labour costs.

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 re-conducted to five major decisions:

- defining the overall warehouse structure in terms of functional departments and their relationships (by analyzing warehouse materials flow);
- warehouse sizing and dimensioning that aim at defining warehouse size and dimensions and its departments;
- defining the detailed layout within each department (i.e. aisle design in the retrieval area, pallet block-stacking pattern in the reserve storage area, configuration of an Automated Storage/Retrieval System, etc.);
- material handling systems design and selection (determination of an appropriate automation level for the warehouse and identification of equipment types for storage, transportation, order picking, and sorting);
- selection of the operational strategies (i.e. the choice between randomized storage or dedicated storage, whether or not use zone picking, the choice between sort-while-pick or sort-after-pick, etc.).

General surveys on warehouse management can be found in Cormier and Gunn (1992), Van den Berg (1999), Rowenhorst et al. (2000), Cormier (2005).

The design of the departments and their functions is part of the definition of the overall warehouse structure (or conceptual design). Main tasks in this case are 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 employ, in order to satisfy storage and throughput requirements and minimize costs.

Warehouse sizing and dimensioning has important implications on construction, inventory management and material handling costs. In particular, warehouse sizing establishes the warehouse storage capacity. Two alternatives can be considered in solving the warehouse sizing problem. In the first case the inventory level is defined externally and, consequently, there is no direct control on the incoming items (e.g. in a third-party warehouse or vendor managed inventory). 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. In the second case, there is a direct control (i.e. an independent wholesale distributor) therefore optimal inventory control 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 and changeable storage size (i.e. the storage size changes over the planning horizon) 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 required floor space 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 model by considering aisle configurations. Rosenblatt and Roll (1984) integrate the optimization model in Bassan *et al.* with a simulation model devoted to evaluate shortage costs as a function of storage capacity and number of zones. Other research studies on warehouse dimensioning can be found in Pliskin and Dori (1982), Azadivar (1989) and Heragu *et al.* (2005). A specific study (also focused on warehouse department dimensioning in a retail store) using advanced 3D simulation tools and artificial intelligence techniques is proposed by Bruzzone and Longo (2010).

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 (doors location, aisles orientation, length, width and number of aisles);
- Automated Storage/Retrieval System configuration, AS/RS (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.

The literature proposes several research works related to the warehouse layout problem. 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 alternative layout designs and extends 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 costs. 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 interesting solutions based both on analytical and simulation approaches can be found in Karasawa *et al.* (1980), Ashayeri *et al.* (1985), Randhawa *et al.* (1991), Randhawa and Shroff (1995), Malmborg (2001).

Material handling systems design and selection is devoted to determine an appropriate warehouse automation level and select equipment for storage, transportation, order picking, and sorting (Cox, 1986; Sharp *et al.*, 1994).

Finally operation strategies have important effects on the overall warehouse performances and are mainly related to storage strategies and picking approaches. As explained in Gu *et al.* (2007), the basic storage strategies include random storage, dedicated storage, class based storage, and Duration-of-Stay (DOS) based storage. 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. Goetschalckx and Ratliff (1990) and Thonemann and Brandeau (1998) demonstrate theoretically that the DOS-based storage policies perform better in terms of internal logistics costs. About zone picking approaches, some interesting research works are reported in Lin and Lu (1999), Bartholdi *et al.* (2000) and Petersen (2000).

It is worth saying that most of the approaches used for warehouse performances evaluation are based on benchmarking, analytical models and simulation and provide information about the quality of the proposed design and/or operational policy in order to

Supply Chain Management Based on Modeling & Simulation: State of the Art and
Application Examples in Inventory and Warehouse Management
101

improve/change it. Warehouse benchmarking is the process of systematically assessing the performance of a warehouse identifying inefficiencies and proposing improvements. A powerful methodology 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), identify the best performance domain and delete the warehouse inefficiencies. Schefczyk (1993), Hackman *et al.* (2001) and Ross and Droge (2002) propose approaches and case studies using DEA for warehouse benchmarking.

Analytical models can be divided into:

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

Finally a number of studies propose advanced tools (also based on simulation) to address warehouse performance evaluation and enhancement problem. Perlmann and Bailey (1988) present a computer-aided design software that allows to quickly generate and compare a set of conceptual design alternatives including building shape, equipment selection and operational policy selection. Linn and Wysk (1990), Wang and Yih (1997) develop expert systems for AS/RS control also based on neural networks. Similarly Ito *et al.* (2002) propose an intelligent agent based simulation system to model a warehouse; the simulation system includes three subsystems: the agent-based communication system, the agent-based material handling system, and the agent-based inventory planning and control system. Additional research work that use simulation based tools are Macro and Salmi (2002) and Hsieh and Tsai (2006). Macro and Salmi present a ProModel-based simulation tool used for analyzing the warehouse storage capacity and rack efficiency. Hsieh and Tsai implement a simulation model for finding the optimum design parameters of a real warehouse system.

The literature survey highlights that, as for the supply chain inventory management, simulation is an enabling technology for investigating the warehouse management problem. The second application example (proposed in the final part of this chapter) investigates the effects of warehouse resources management on warehouse efficiency highlighting as the interactions among operational strategies and available resources strongly affect the internal logistic costs.

2.3 Critical issues in supply chain Modeling & Simulation

As final part of the state of the art overview, in this section some critical issues in supply chain Modeling & Simulation are presented and discussed. The Modeling & Simulation (M&S) based approach for studying supply chains has to be:

- flexible and parametric for creating and investigating different supply chain scenarios;
- efficient in terms of time required for simulation runs execution even in correspondence of complex supply chains (i.e. high number of supply chain stages, high numbers of items, etc.);
- repetitive in its architecture for easily changing the number of supply chain echelons and the supply chain configuration.

A supply chain simulator that aims at reaching such features should pay attention to the modeling approach. Let us consider the traditional modeling approach proposed by two of

the most used commercial discrete event simulation packages, Em-Plant (by Siemens-UGS) and Anylogic (by Xj-Technologies). Both of them propose a typical object oriented modeling approach. Each discrete event simulation model (developed by using these software) is made up by system state variables, entities and attributes, lists processing, activities and delays. Let us focus on entity, it can be dynamic (it moves through the system) or it can be static (it serves other entities, generally called resources) and it may have attributes for recording specific information (Banks, 1998). Typically, supply chain simulation models can involve a high number of dynamic entities (i.e. for modeling the flow of items and information) and, in comparison with the previous ones, a small number of resources (stores, plants, warehouses). Even if the simulation model is being used for analyzing a single supply chain node the number of dynamic entities is usually greater than the number of static entities. Consider a production plant, the number of work pieces is usually greater than the number of machines; similarly in a marine container terminal the number of containers is remarkable greater than the number of berth and yard resources.

Each single dynamic entity corresponds to an object flowing in the simulation model. As soon as the number of dynamic entities becomes high, the time required for executing a simulation run becomes unacceptable. In addition, library objects (used for modeling static entities) very often fall short of recreating the real system with satisfactory accuracy. In other words, it can happen that the traditional modeling approach (proposed by a number of discrete event simulation packages), in terms of library objects and dynamic entities, presents two main problems: (i) difficulties in modeling complex scenarios; (ii) too many entities cause computational heavy models. In the remainder of the chapter, as part of the description of the first application example (and as a part of a successful approach to develop supply chain simulation models), an advanced modeling approach for developing flexible, time-efficient and parametric supply chain simulators is proposed.

3. From the supply chain conceptual model and inventory models definition to the supply chain simulation

Sections 3 and 4 present the first application example in which a supply chain simulation model is used for investigating a comprehensive set of operative scenarios including different inventory control policies under customers' demand intensity, customers' demand variability and lead times constraints. The application example is mainly based on simulation studies already carried out, some years ago, by the author (Longo and Mirabelli, 2008; De Sensi et al., 2008).

In order to provide the reader with a logic and easy-to-read structure, in our treatment, the same set of steps of a simulation study described by Banks (1998) are adopted. The list is as follows:

- problem formulation;
- setting of objectives;
- model conceptualization;
- data collection;
- model translation;
- verification, simulation run length and validation;
- experimental design;
- simulation runs and analysis.

We have already introduced the problem formulation and the objectives of the study proposed in this chapter, highlighting (by means of the state of the art survey) the contribution to the literature.

Therefore, in the sequel, a supply chain conceptual model, that includes four different inventory models, is presented and discussed. In our supply chain conceptual model a single network node can be considered as store (ST), distribution center (DC) or plant (PL). A supply chain begins with one or more PLs and ends with one or more STs. Usually STs satisfy market demand or demand from other STs, DCs satisfy STs demand or demand from others DCs and PLs satisfy DCs demand and demand from other PLs. By using these three types of supply chain nodes we can model a whole supply chain. Let us briefly consider the conceptual model of each supply chain node.

3.1 Stores, distribution centers and plants conceptual models

Starting from the end of the supply chain, the arrival process of market demand at STs is Poisson and the quantity required for each item is triangular with different levels of intensity and variability. Once customers arrive at stores, the quantity required is compared with the on hand inventory and the order is eventually satisfied (lost quantity are recorded for fill rate calculation). Just before the ST business hour (8:30 AM) the inventory is updated with deliveries from DCs or other STs. Just after the ST business hour (4:30 PM) the inventory is checked using one of the available control policies. In case of purchase order emission, it is required to choose the distribution center or the store toward which the order will be emitted. Such decision is taken considering the lead time, the lead time demand and the quantity that DCs or stores can replenish. Note that the lead time demand can be evaluated by using different forecast methods (i.e. single exponential smoothing, double exponential smoothing, triple exponential smoothing, moving average, etc.). The quantity received can be different from the quantity ordered due to problems at PLs, DCs or STs. Figure 1 shows the operations flow chart including logics and rules governing ST behavior.
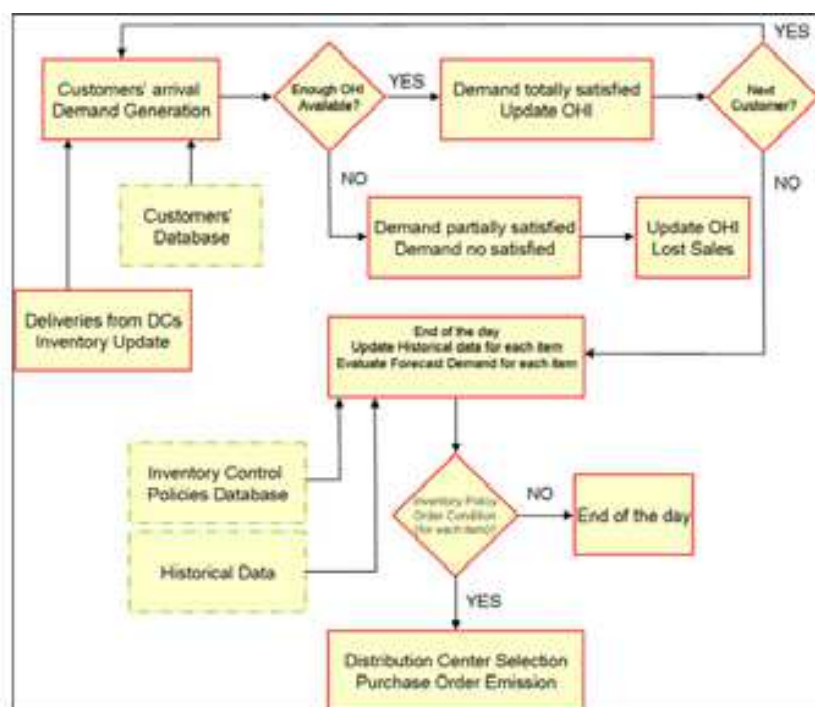

Fig. 1. Operations flow chart including logics and rules governing STs behavior

The DCs operate according to the following logic. Every day the supply chain DCs try to satisfy purchase orders. Items distribution is performed according to the same priority index for all the supply chain nodes. In other words, if the on hand inventory of item j is not enough for satisfying nodes demand, the available quantity is divided proportionally to quantity required. Lost quantities are recorded, thus, the distribution center performance measures, such as fill rate, can be easily calculated. The inventory is checked using one of the available control policies. The purchase order emission requires a decision on which PL or DC to send the order and the evaluation of the lead time demand. PL selection is made according to PLs and machines performances and working queues. DC selection is made according to lead time and quantity that can be replenished. Once again, the order is sent toward the PL or DC that assures the highest quantity in the shortest time. Figure 2 shows the operations flow chart including logics and rules governing DC behavior.
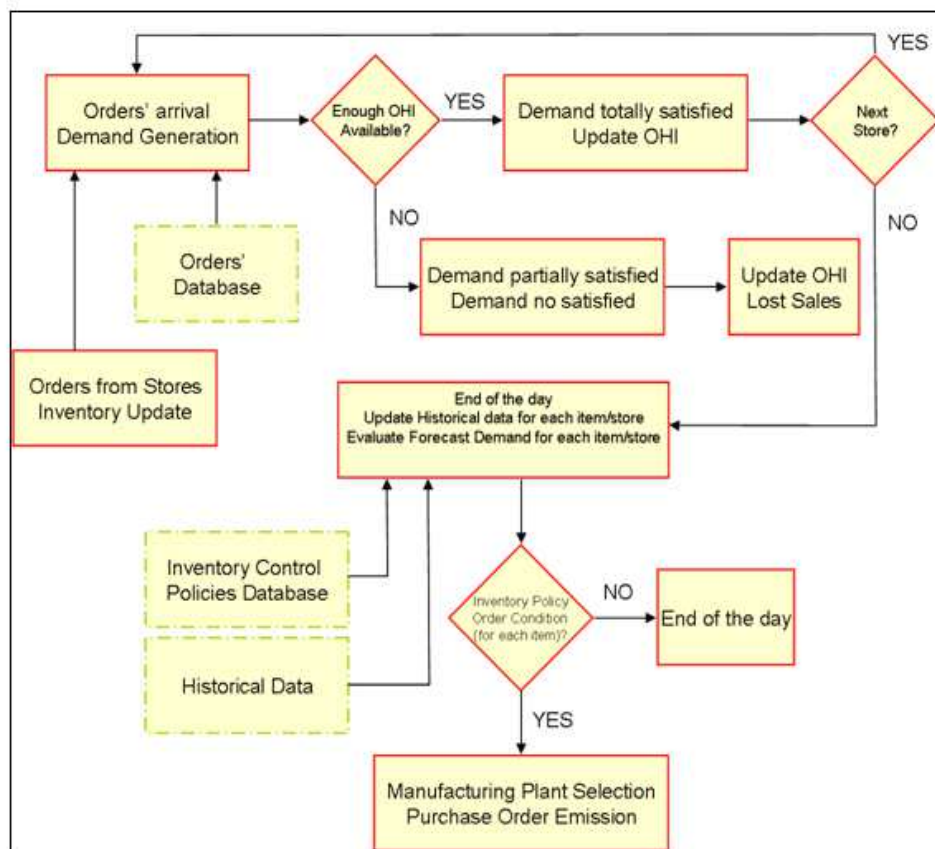

Fig. 2. Operations flow chart including logics and rules governing DCs behavior

Finally PLs behave as described below. Each production order waits in a queue and it is sent to a distribution center (or plant) just after the production. Each PL has a certain number of machines and each machine can manufacture all the types of items (with different efficiency, working times and setup times when switching from a product to another). The PLs inventory management is similar to DCs inventory management. Different inventory control policies, demand forecast methods and lead times are available. Figure 3 shows the operations flow chart including logics and rules governing PLs behavior.
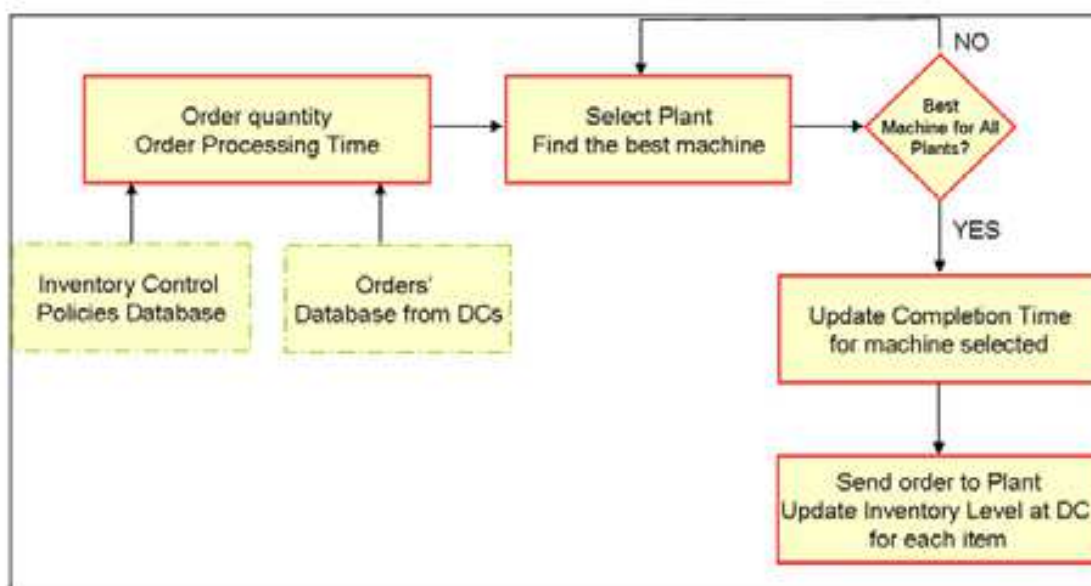
Fig. 3. Operations flow chart including logics and rules governing PLs behavior

3.2 Inventory control policies definition

Let us consider now the inventory control policies. Four different inventory control policies are considered and implemented within each supply chain node: (i) continuous review with re order point equals to the target level and constant safety stock, rR1; (ii) continuous review with re order point equals to the target level and variable safety stock, rR2; (iii) continuous review with fixed review period for policy parameters, rR3; and, (iv) continuous review with optimized review period for policy parameters, rR4.

The inventory management at each node of the supply chain has to answer to three different questions: (i) how often to review the stock status; (ii) when to order new products; (iii) quantity of new products. Before getting into inventory policies details let us define the following notations:

- $rl_{ij}(t)$, re-order level at time t of the item j at the network node i;
- $RL_{ij}(t)$, target level at time t of the item j at the network node i;
- $SS_{ij}(t)$, safety stock at time t of the item j at the network node i;
- $OHI_{ij}(t)$, on hand inventory at time t of the item j at the network node i;
- $QO_{ij}(t)$, quantity already on order at time t of the item j at the network node i;
- $QS_{ij}(t)$, quantity to be shipped at time t of the item j at the network node i;
- $Q_{ij}(t)$, quantity to be ordered at time t of the item j at the network node i;
- $D_{ij}(t)$, customers' demand at time t of the item j at the network node i;
- $DF_{ij}(t)$, demand forecast at time t of the item j at the network node i;
- LT_{ij}, lead time of the item j at the network node i;

The evaluation of $Q_{ij}(t)$ has to take into consideration the quantity already on order and the quantity to be shipped, so the correct measure to be used is the Inventory Position defined in (1).

$$IP_{ij}(t) = OHI_{ij}(t) + QO_{ij}(t) - QS_{ij}(t) \qquad (1)$$

The calculation of $Q_{ij}(t)$ requires the calculation of the demand forecast, $DF_{ij}(t)$, over the lead time. The Lead Time Demand of the item j at network node i, $LTD_{ij}(t)$, is evaluated by using the single exponential smoothing methodology. We can write:

$$LTD_{ij}(t) = \sum_{k=t+1}^{t+LT_{ij}} DF_{ij}(k) \tag{2}$$

As before mentioned, four different inventory control policies are investigated. Each policy is based on the continuous review approach (the inventory is reviewed continuously and the time axis is modeled continuously).

Continuous review with re-order level equals to target level and constant safety stock (rR,1)

An inventory control policy has to answer three different questions: how often to check the inventory status, instant of time for purchase order emission and quantity to be ordered. The first question is easily answered; in this case the inventory is checked continuously. The second question is answered by condition expressed in equation (3). The quantity to be ordered is evaluated in equation (4). The safety stock is calculated as standard deviation of the lead time demand. In this policy SS_{ij} is constant.

$$IP_{ij}(t) < rl_{ij}(t) = RL_{ij}(t) = LTD_{ij}(t) + SS_{ij} \tag{3}$$

$$Q_{ij}(t) = RL_{ij}(t) - IP_{ij}(t) = LTD_{ij}(t) + SS_{ij} - IP_{ij}(t) \tag{4}$$

Continuous review with re-order level equals to target level and variable safety stock (rR,2)

The purchase order emission and the quantity to be ordered follow equations (3) and (4). The safety stock is calculated as the standard deviation of the daily demand times the safety time. The safety time is the Lead Time plus the standard deviation of the Lead Time multiplied by a factor expressing the service level that should be provided at the supply chain node.

Continuous review with fixed review period (rR,3)

The re-order level, the target level and the safety stock are supposed to be constant over the review period (RP). Let us indicate the demand forecast over RP with $RPD_{ij}(t)$. We can write:

$$rl_{ij}(t) = LT_{ij} * \frac{RPD_{ij}(t)}{RP} + SS_{ij}(t) \tag{5}$$

$$RL_{ij}(t) = \frac{RPD_{ij}(t)}{RP} + rl_{ij}(t) \tag{6}$$

The emission condition of the purchase order is reported in (7) and the quantity to be ordered in (8).

$$IP_{ij}(t) < rl_{ij}(t) \tag{7}$$

$$Q_{ij}(t) = RL_{ij}(t) - IP_{ij}(t) \tag{8}$$

Continuous review with optimized review period (rR,4)

In addition to the traditional continuous review control policies, we propose an optimized review period based approach. Let us consider the inventory costs described as follows.

- $C_{ij,o}$, order placing cost for item j at the network node i;
- $C_{ij,t}$, transportation cost for item j at the network node i;
- $C_{ij,r}$, order reception cost for item j at the network node i;
- $C_{ij,st}$, storage cost for item j at the network node i;
- $C_{ij,w}$, worsening cost for item j at the network node i;
- $C_{ij,ob}$, obsolescence cost for item j at the network node i;
- $C_{ij,i}$, interest cost for item j at the network node i;
- P_{ij}, price for the item j at the network node i;

Let us define the total cost for purchase order emission (9) and the total cost for storage (10). We can write:

$$TC_{POE,ij} = C_{ij,o} + C_{ij,t} + C_{ij,r} \qquad (9)$$

$$TC_{ST,ij} = C_{ij,st} + C_{ij,w} + C_{ij,ob} + C_{ij,i} \qquad (10)$$

The optimized review period, $ORP_{ij}(t)$, can be calculated trying to minimize, on the basis of demand forecast, the unitary inventory cost $UIC_{ij}(t)$, that is

$$UIC_{ij}(t) = \frac{TC_{POE,ij} + TC_{ST,ij} * \sum_{t}^{t+T-1}(t-1)*DF_{ij}(t)}{\sum_{t}^{t+T-1} DF_{ij}(t)} = MIN \qquad (11)$$

The value of T that minimizes $UIC_{ij}(t)$ is the $ORP_{ij}(t)$. Let us indicates with $ORPD_{ij}(t)$ the forecast demand over the optimized review period, the reorder level and the target level can be calculated using equations (12) and (13).

$$rl_{ij}(t) = LTD_{ij} + SS_{ij}(t) \qquad (12)$$

$$RLij(t) = ORPD_{ij} + rl_{ij}(t) \qquad (13)$$

In other words the $ORPD_{ij}(t)$ is the optimal lot size calculated by means of demand forecast. The first term of the sum in equation (13) is recalculated every $ORPD_{ij}(t)$ 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 (7) and (8).

3.3 Data collection and analysis
Data collection in a whole supply chain is one of the most critical issues. The random behaviour of some variables makes the supply chain a stochastic system. As reported by Banks (1998), for each element in a system being modelled, the simulation analyst must decide on a way to represent the associated variables. The Data Collection step takes care of collecting data in each supply chain node as well as finds the most suitable computer representation for such data.

Usually there are three different choices: (i) data are deterministic or data are considered as deterministic, (ii) a distribution probability is fitted to empirical data and (iii) the empirical distribution of the data is directly used in the simulation model.

In our treatment, the supply chain is characterized both by deterministic data and stochastic data (both numerical data and inputs that drive the logics of the supply chain). Therefore, the second and the third choices are adopted for representing, in the simulation model, supply chain stochastic variables.

In case of stochastic variables and distributions fitting, the procedure for input data analysis is the classical procedure proposed by many statistics references as well as implemented in all statistics software. Starting from the histogram of the data, one or more candidate distributions are hypothesized; for each distribution the characterizing parameters are estimated and a goodness of fit test is preformed. Finally, the best distribution is chosen. For any additional information on input data analysis for simulation studies please refer to Johnson et al. (1992, 1994, 1995) and D'Agostino and Stephens (1986).

Table 1 consists of a list of the most important variables and information collected for each plant, distribution center and store. Most of the data have been obtained using companies' informative systems. The data in *italicized style* are characterized by stochastic behaviour. As example of the input data analysis procedure, consider the market demand arrival process. Customers' inter-arrival times are collected and fitted using the above mentioned procedure for each store.

Plants	Distribution centers	Stores
List of operations	List of operations	List of operations
Process Time	*Lead Time*	*Demand arrival process*
Setup Time	Inventory Control Policy	*Customer demand*
Lead Time	Forecast Method	*Lead Time*
Number and type of machines	Inventory Costs	Inventory Control Policy
Bill of materials	Items mixture	Forecast Method
Items mixture		Inventory Costs
		Items mixture

Table 1. Data Collection in each supply chain echelon.

Let us focus on the store #1. Starting from the histogram of the data (based on 21 classes, see figure 4) four different distributions are hypothesized: Erlang, Weibull, Negative Exponential and Lognormal. The collected data allow the calculation of the distributions parameters, summarized in table 2. The successive step is the goodness of fit test. Note that we deal with a large sample so the Chi-Square test performs better than Ardenson-Darling and Kolmogorov-Sminorv tests. As well known from statistics theory if the *Chi Statistics* is lower than the *Chi Value*, the distribution accurately fit the real data. The Result column in table 2 shows that the Erlang and Negative Exponential distributions perform a good fit of the data. In presence of two or more available distributions, the choice falls on the distributions with lowest *Chi Statistics*. In our case, the Negative exponential distribution has been selected for representing customers' inter-arrival times for store #1.

As final result, we obtained that, for each store, the customers' inter-arrival process is well represented by a Poisson process (numerous scientific works confirm such results for inter-arrival times). Due to high number of items, the data regarding the quantity required by customers have been analyzed in terms of minimum, average and maximum values (triangular distributions). Each customer can require each type of item; items mixture is represented in the simulation model with empiricaldistributions. Lead times have been
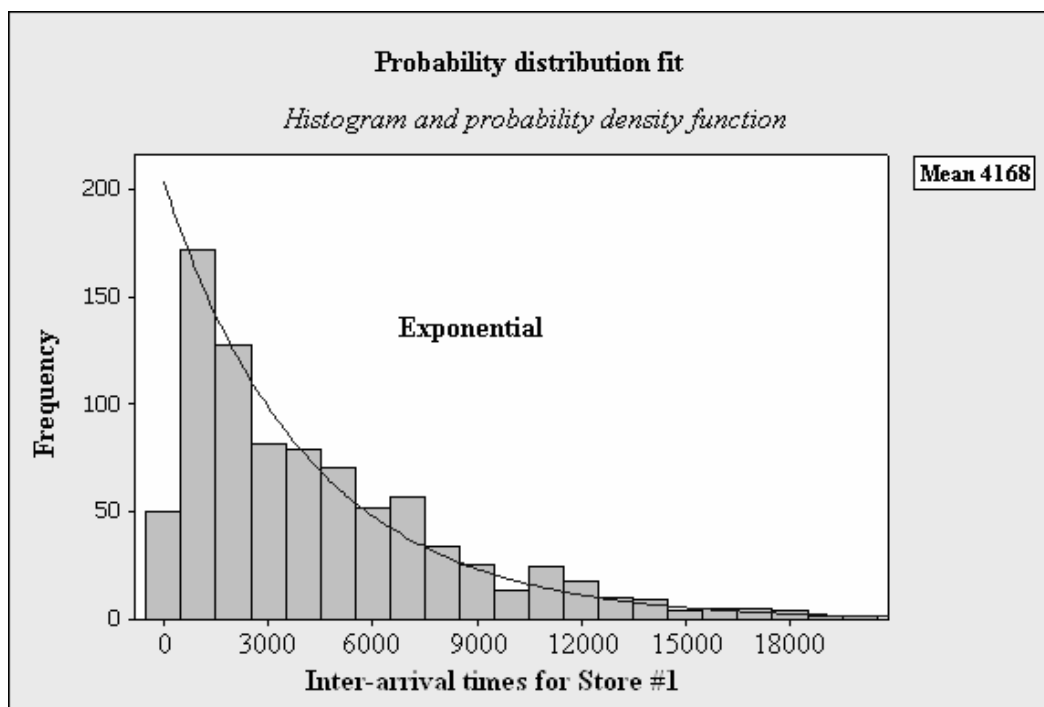
Supply Chain Management Based on Modeling & Simulation: State of the Art and
Application Examples in Inventory and Warehouse Management
109

Fig. 4. Histogram and Distribution fitting for customers' inter-arrival times at Store #1

Distributions	Chi Statistics	Chi Value	Results	Parameter 1	Parameter 2
Erlang	18.419	24.997	true	4163.164	4163.164
Weibull	25.925	24.997	false	1.009	4184.344
Negexp	16.315	26.297	true	4168.058	
Lognorm	129.001	24.997	false	5383.540	11142.929

Table 2. Distribution fitting for store #1: Chi-square goodness of fitting test and distribution parameters

fitted with normal distributions. Plants process times and setup times use empirical distributions. Table 3 consists of statistic distributions and parameters related to collected data. Note that the triangular distribution is reported (as example) only for item #1. Analogous information are available for each item

Variables	Distribution Type	Parameters estimation
Inter-arrival time	Neg. Expon.	m = 1.16 hours (mean inter arrival time)
Quantity (item#1)	Triangular	min = 21, mean = 30, max = 40 pallets
Item mixture	Empirical	
Lead Time (Plants)	Gaussian	m = 2 days (mean value); s = 0.4 days (stand. dev.)
Lead Time (DCs)	Gaussian	m = 3 days (mean value); s = 0.5 days (stand. dev.)
Process Time (Plants)	Empirical	
Setup Time (Plants)	Empirical	

Table 3. Statistic distributions and parameters for collected data

3.4 Modeling the stores, the distribution centers and the plants

The following section deals with the supply chain conceptual model translation into a computerized simulation model. The commercial discrete event simulation software eM-Plant (by Siemens-UGS) is used and an advanced modeling approach is presented and discussed. Despite the specific simulation software used, the modeling approach proposed in the sequel can be easily adapted and used with all the discrete event simulation software that provide the user with a programming language (specific or general purpose).

The modeling approach proposed by eM-Plant is object oriented (as most of the modeling approach proposed by discrete event simulation software). The translation of the conceptual model in a computer simulation model could be performed using library objects. Specific classes could be implemented for STs, DCs and PLs; the supply chain flow of items and information could be modeled by means of dynamic entities. Using such approach we should pay attention to the number of dynamic entities flowing in the simulation model; the higher is the number of dynamic entities, the lower is the simulation model speed and the higher is the total time required for executing a simulation run.

In our treatment an advanced modeling approach based on programming code, tables and events generators is proposed. eM-Plant provides the user with the simulation languages Simple++ that can be used for writing specific routines, called methods. The methods, by means of programming efforts, allow to correctly translating the supply chain conceptual model. The supply chain flow of dynamic entities, representing items and information, is substituted by information recorded in tables. Without the flow of dynamic entities, simulation events are generated using event generator objects (provided by the library) and, in correspondence of such events, the methods elaborate and update the information stored in tables. Following this modeling approach we obtain a flexible, parametric (every class object can be easily accessed and modified for adding new features) and time efficient simulation model (some results in term of time for executing a simulation run, will be discussed later). To give the reader an idea of the modeling approach, let us now examine the simulation model architecture, made up of five different classes: *Store*, *Distribution Center*, *Plant*, *Simulation Model Interface* and *Simulation Model Main Frame*.

The upper part of figure 5 shows the store modeling frame. It has been subdivided in three main sections: *Customer Manager, Inventory Manager, Database Results* (the description proposed below will be useful for those readers interested in developing similar approaches, it can be neglected by the others interested only in dealing with supply chain inventory problems).

The object *CustomersArr* is an event generator. It generates the customers' arrival process (if the store is at the end of the supply chain). The methods *CustArr* and *CustManager* take care of customers' demand checking the on hand inventory and recording all the orders information in the table *CustOrders* (see figure 5). Every day, just after the store business hour, the object *InvMan* generates the event for starting the inventory control process. The method *InvManager* checks the inventory using the inventory control policy selected by the user. The method *InvManager* is supported by the method *ParEval* for evaluating the policy parameters, $rl_{ij}(t)$, $RL_{ij}(t)$, $SS_{ij}(t)$ and by the method *DemForec* for evaluating the lead time demand, $LTD_{ij}(t)$ (stored in the table *Forecasts*). In case of order emission, the method *PurchaseOrder* is called and the purchase order is recorded in the table *PurchaseOrders*. The method *DCChoice* chooses the best distribution center or store in terms of quantity and lead time and sends the purchase order to the distribution center or store chosen. Every morning, just before the store business

hour, the object *InventoryUp* generates the event for starting the inventory update. The table *PurchaseOrders* is checked for deliveries and the inventory is eventually updated. The inventory information are stored in the table *Inventory* (see figure 5). At the end of the day, the store performance measures are collected in the table *Data_Day*.

CustOrders table

CO_ID (Customer Order ID)	Date and Time	Item Ordered (ID)	Quantity	Order Condition	Lost Sales Quantity
1	2005/05/02 09.43.19.4213	1	40	Fully satisfied	
2	2005/05/02 09.43.19.4213	2	32	Fully satisfied	
3	2005/05/02 09.43.19.4213	3	33	Fully satisfied	

Inventory table

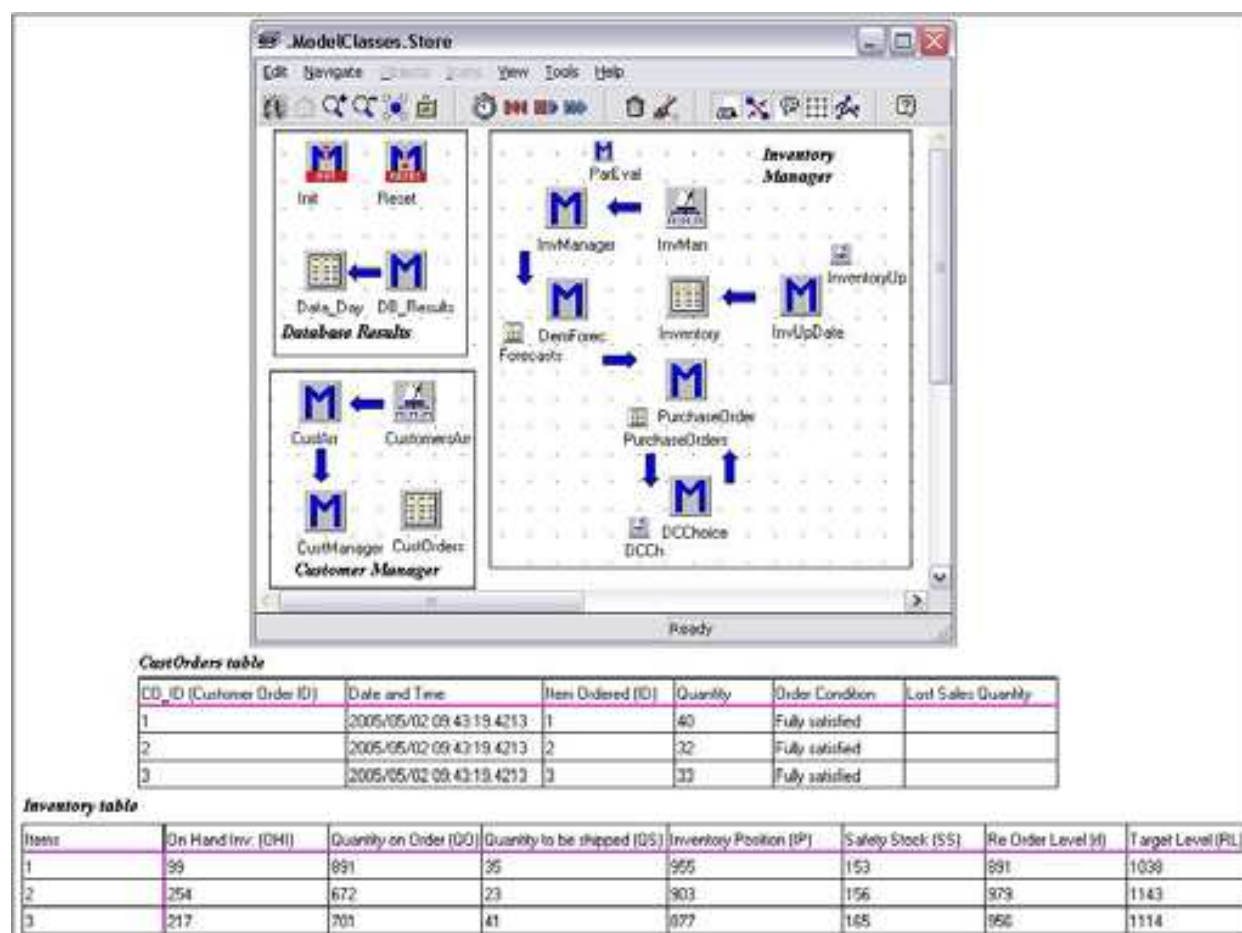| Items	On Hand Inv. (OHI)	Quantity on Order (QO)	Quantity to be shipped (QS)	Inventory Position (IP)	Safety Stock (SS)	Re Order Level (rl)	Target Level (RL)
1	39	891	35	955	153	891	1039
2	254	672	23	903	156	979	1143
3	217	703	41	977	165	956	1114

Fig. 5. Store Modeling frame and examples of information stored in tables.

The same architecture is implemented for the Distribution Center class, even if there are some variables and methods with different names. The Plant class proposes the same modeling approach; in addition, in this class we have implemented the *Manufacturing Manager* section for plant machines modeling and management. The same modeling approach for STs, DCs and PLs guarantees high flexibility if the supply chain echelons number has to be modified or different supply chain echelon has to be considered.

Note that the use of dynamic entities flowing in the simulation model dynamic entities is completely eliminated. Stores, Distribution Centers and Plants classes instantiated in the model have different identifying numbers that allow the information exchange protocol to work correctly.

As already mentioned, flexibility in terms of supply chain scenarios definition is a critical issue for simulation models that must be used as decision-making tool. Now, we examine how a supply chain manager can define alternative supply chain scenarios by using a *Simulation Model Interface* (see figure 6). Again, the description proposed below would be interesting for those readers interested in developing similar approaches. The main dialog of the *Simulation Model Interface* provides the user with many commands as, for instance,

number of items, simulation run length, start, stop and reset buttons and a Boolean control for the random number generator (to reproduce the same experiment conditions in correspondence of different operative scenarios). The supply chain conceptual model considers a three -echelon supply chain made up by stores, distribution centers and plants. Three different dialogs can be activated respectively by clicking on the tree buttons *Stores data input, Distribution Centers data input* and *Plants data input* (see fig. 6). Thanks to these dialogs, the user or supply chain manager can set the number of supply chain echelons, nodes position in the supply chain, total number of network nodes and all numerical values, input parameters and information in specific tables.
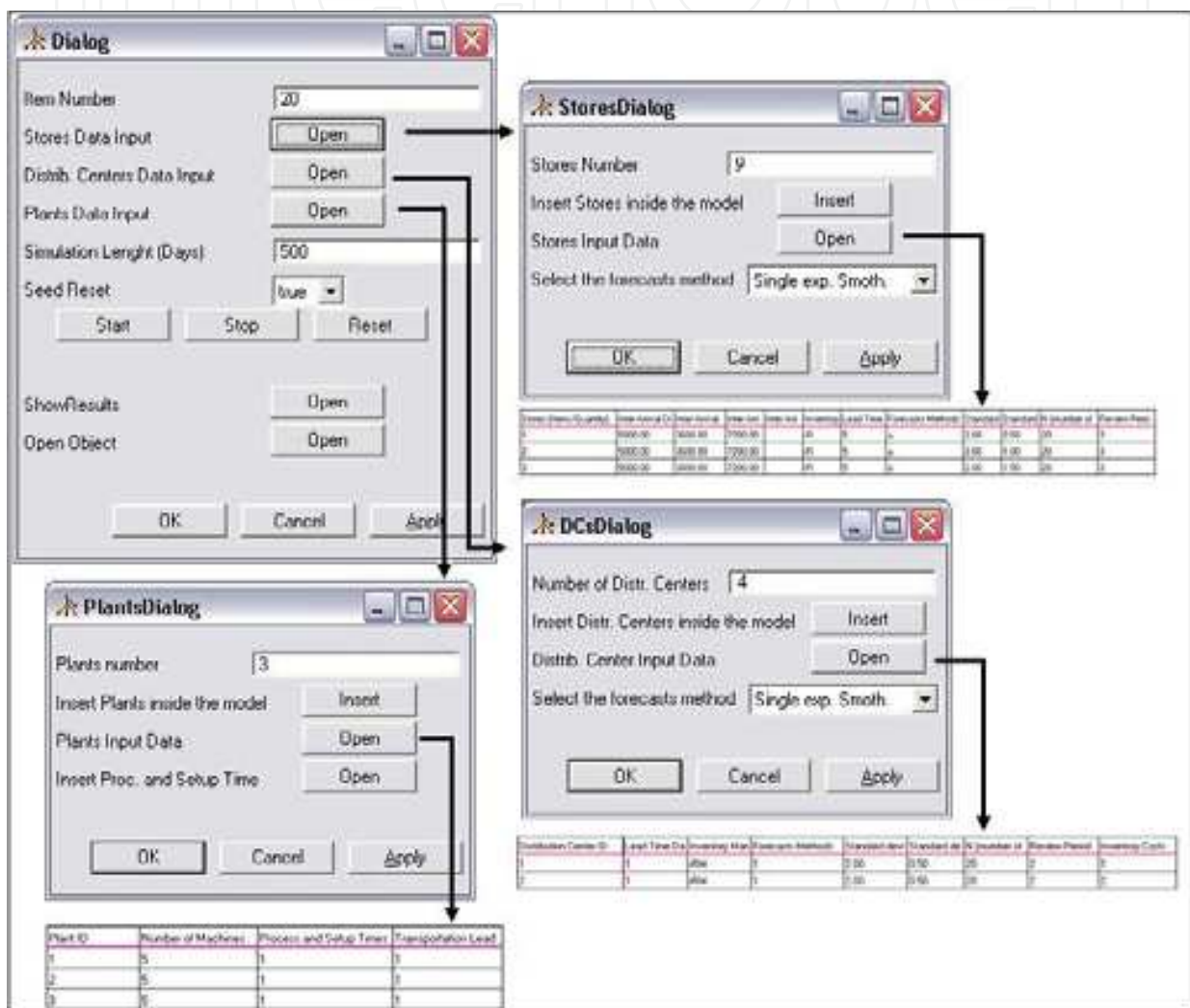

Fig. 6. Simulation Model Interface

After the definition of the supply chain scenario, the supply chain can be created simply by clicking (in each dialog) the insert button. The user-defined scenario is automatically recreated; instances of the classes *Store, DistributionCenters* and *Plants* are inserted within the *Simulation Model Main frame* (see figure 7). The Simulation Main Frame also shows an indicator of date, time and day of the week. The user can access the simulation interface object at every moment for changing the supply chain scenario; similarly each node of the supply chain can be accessed during the simulation for real-time monitoring all the supply chain information and performance measures stored in tables.
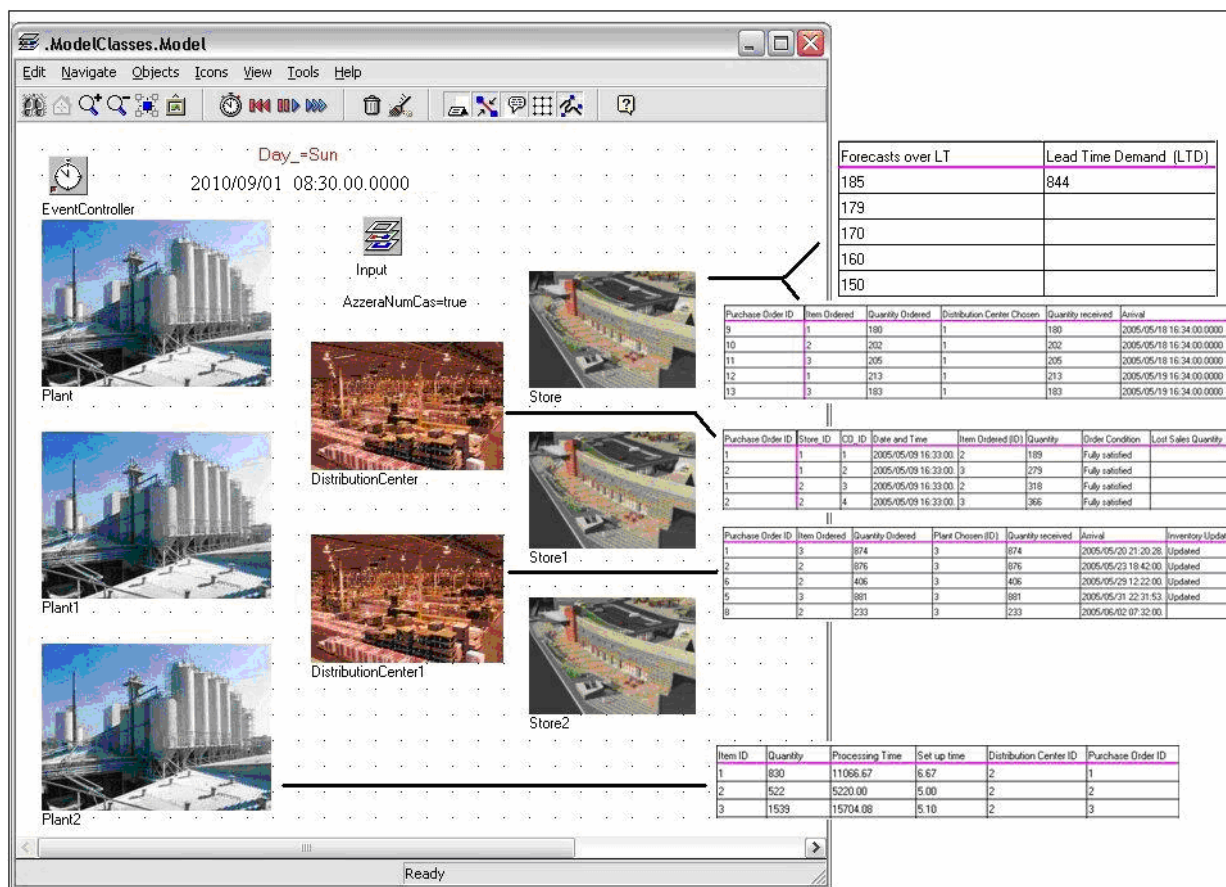
Fig. 7. Simulation Model Main frame and information stored in tables

Note that the high flexibility of the simulation model in terms of scenarios definition is one of the most important features for using it as a decision-making tool. The simulator interface object gives to the user the possibility to carry out a number of different what-if analysis by changing supply chain configuration and input parameters (i.e. inventory policies, demand forecast methods, demand intensity and variability, lead times, inter-arrival times, number of items, number of stores, distribution centers and plants, number of supply chain echelons, etc.).

Note that, in case of information sharing along the supply chain, the user can directly use the real supply chain node as empirical data source. When no data are available, one possibility is to obtain subjective estimates by means of interview to supply chain experts and data collection. Estimates made on the basis of assumptions are strictly tentative (Banks, 1998). In this case, the simulation model should be tuned for recreating as much as possible the real supply chain (this is a typical situation in the case of both theoretical research studies and real supply chain applications).

All the performance measures can be directly accessed inside the main frame of each supply chain node: the user can see what is going on inside each supply chain node in terms of fill rates, on hand inventory, inventory position and safety stocks for each items. In addition, all the results can be easily exported in Microsoft Excel and analyzed by using chart and histograms. Different Microsoft Excel spreadsheet has been programmed with *Visual Basic Macro* for simulation results collection and analysis in terms of performance measures average values and confidence intervals.

3.5 Simulation model verification, run length and validation

The accuracy and the quality throughout a simulation study are assessed by conducting verification and validation processes (Balci 1998). The American Department of Defence Directive 5000.59 defines verification and validation as follows. "Verification is the process of determining that a model implementation accurately represents the developer's conceptual description and specifications". Obviously, this step is strictly related to model translation. "Validation is the process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended use of the model". Problems during the validation phase can be attributed to model conceptualization or data collection. In our treatment, according to the published literature, the verification and validation has been conducted throughout the entire lifecycle of the simulation study and using both dynamic and informal verification and validation techniques.

The simulation model verification is made using a dynamic technique (debugging). As explained in Dunn (1987), debugging is an iterative process that aims to find model errors and improve the model correcting detected 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 (Simple++ programming code) have been iteratively debugged line by line, detecting and correcting all the errors. Errors detected during the simulation study life cycle were mostly due to: misunderstanding or numerical error in input data, tables and spreadsheet indexes management, events list organization and management. In addition, before model translation, logics and rules governing supply chain behaviour have been discussed with supply chain' experts.

Before getting into details of simulation model validation, we need to introduce and discuss the simulation run length problem. 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 simulation runs. The run length has been correctly determined using the mean square pure error analysis (MS_{PE}). 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. In our case, the experimental error of the supply chain performance measures (i.e. fill rate and average on hand inventory), must be considered.

The simulation model calculates the performance measures for each supply chain node, thus, the MS_{PE} analysis has to be repeated for each supply chain node and for each performance measure. The MS_{PE} curve, that takes the greatest simulation time for obtaining negligible values of the mean squares pure error, defines the simulation run length. Figure 8 shows the MS_{PE} curve of distribution centre #2 that takes the greatest simulation time. After 500 days the MS_{PE} values are negligible and further prolongations of the simulation time do not give significant experimental error reductions.

Choosing for each simulation run the length evaluated by means of MS_{PE} analysis (500 days), the validation phase is conducted using the *Face Validation* (informal technique). For each retailer and for each distribution centre the simulation results, in terms of fill rate, are compared with real results. For a better understanding of the validation procedure, let us consider the store #1. Figure 9 shows six different curves, each one reporting the store
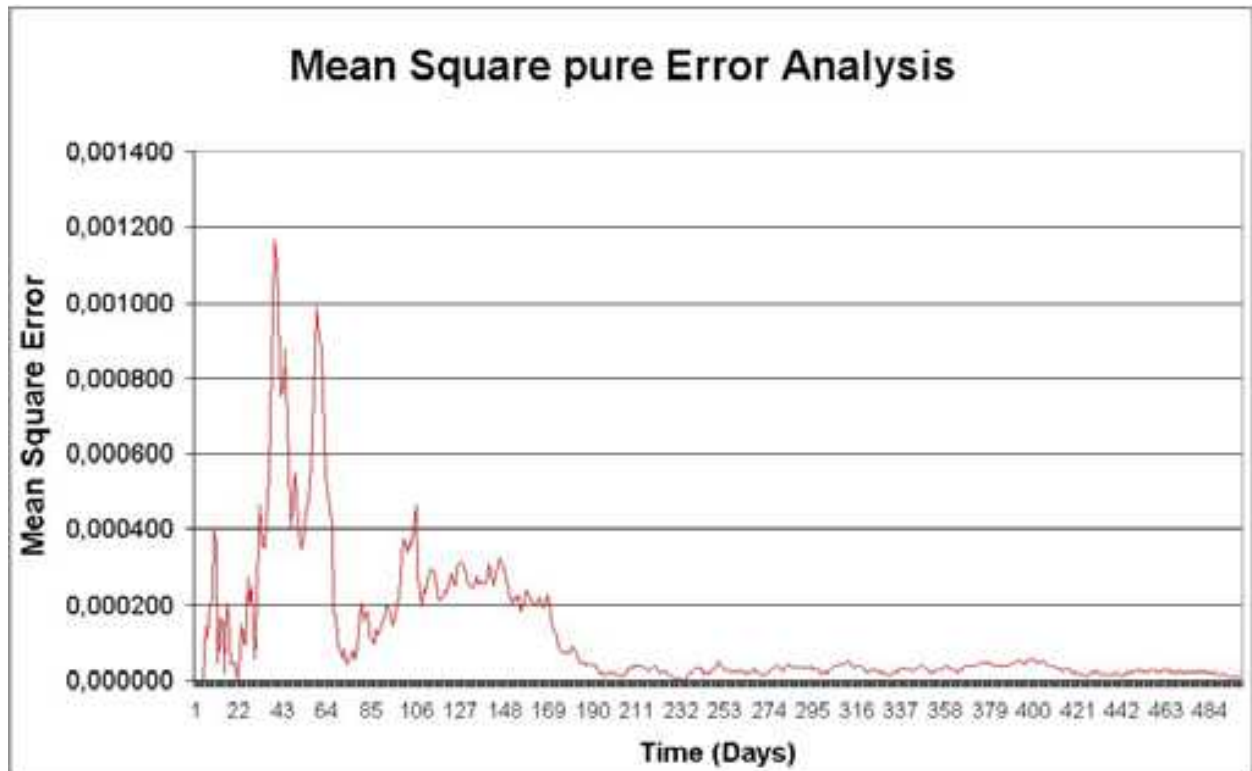
Fig. 8. Mean Square Pure Error Analysis and Simulation Run Length

#1 fill rate versus time (days). In the graphs there is one real curve and five simulated curves (note that during the validation process the simulation model works under identical input conditions of the real supply chain).
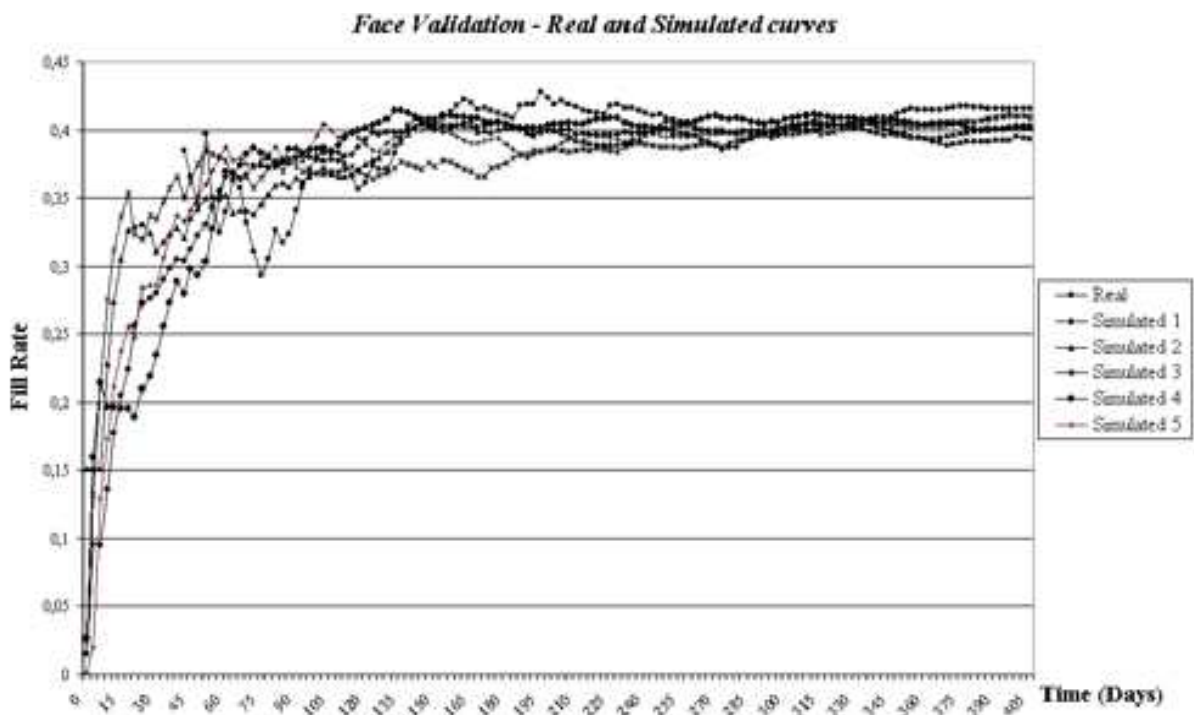

Fig. 9. Main effects plot: Store #1 fill rate versus inventory control policies, lead time, demand intensity and demand variability

The plot is then shown to the supply chain's experts asking them to make the difference between the real curve and the simulated curves on the basis of their estimates (obviously showing all the curves without identification marks). In our case the experts were not able to see any difference between real and simulated curves, assessing (as consequence) the validation of the simulation model. The Face Validation technique has been applied for the remaining stores 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 supply chain.

4. Experimental design, simulation runs and analysis

The first application example (proposed in this section) is a focus on the inventory problem within the three-echelon stochastic supply chain presented above. The supply chain simulation model is used for investigating a comprehensive set of operative scenarios including the four different inventory control policies (discussed in section 3.2) under customers' demand intensity, customers' demand variability and lead times constraints. The application example also shows simulation capabilities as enabling technology for supporting decision-making in supply chain management especially when combined with Design of Experiment, DOE, and Analysis of Variance, ANOVA for simulation results analysis.

In this application example, nine stores, four distribution centers, three plants and twenty items form the supply chain scenario. Before getting into simulation results details, let us give some information about the simulation model efficiency in terms of time for executing a simulation run. Each 500 days replication takes about one minutes (running on a typical commercial desktop computer). If the number of replications is three, a simulation run is over in 3 minutes. Our experience with supply chain simulation models developed using eM-Plant (Longo, 2005a, 2005b), suggests simulation times higher then 10 minutes if the traditional modeling approach is selected. Having obtained such times is not difficult to carry out complete design of experiments using the full factorial experimental design.

Let us consider for each supply chain node four different parameters: the inventory control policy, the lead time, the market demand intensity and the market demand variability and let us call these parameters factors (in literature factors are also called treatments). In this study, we have chosen, for each factor, different number of levels as reported in table 4.

Factors	Levels			
Inventory Control Policy (x_1)	rR,1	rR,2	rR,3	rR,4
Stores Lead Time (x_2)	1	3	5	
Customers' Demand Intensity (x_3)	Low	Medium	High	
Customers' Demand Variability (x_4)	Low	Medium	High	

Table 4. Factors and Levels

Note that the simulation model user can easily define a different supply chain scenario by changing the number of echelons, the number of STs, DCs and PLs, the number of items or select different parameters (i.e. demand forecast methodologies, transportation modalities, priority rules for ordering and deliveries, etc.). Analogously new parameters or supply chain features can be easily implemented thanks to simulator architecture completely based on programming code. The objective of the application example is to understand the effects of factors levels on three performance measures: fill rate (Y_1), average on hand inventory

(Y_2) and inventory costs (Y_3). The outcomes are input-output analytical relations (called the meta-models of the simulation model).

In our application example, checking all possible factors levels combinations (full factorial experimental design) requires 108 simulation runs; if each run is replicated three times we have 324 replications. Having set the simulation model for executing three replications for each simulation run and considering all the factors levels combinations, we have executed, on a single desktop computer, all the experiments taking less than 6 hours. Note that, very often, pre-screening analyses reduce the number of factors to be considered as well as fractional factorial designs reduce the total number of simulation runs. The efficiency of the simulation model in terms of time for executing simulation runs is largely due to the simulation model architecture and modeling approach.

Monitoring the performance of an entire supply chain requires the collection of a huge amount of simulation results. To give the reader an idea of the simulation results generated by the simulation model in our application example, let us consider the fill rate: the simulation model evaluates the fill rate at the end of each replication, as mean value over 500 days. For each supply chain node (both STs and DCs) and for each simulation run (a single combination of the factors levels) the model evaluates 3 fill rate values (9 stores x 4 DCs x 109 simulation runs x 3 replications = 11772 values). Consider the average on hand inventory: the simulation model evaluates, at the end of each replication, the mean value over 500 days. For each supply chain node, for each simulation run and for each item, 3 values of the performance measures are collected (9 stores x 4 DCs x 109 simulation runs x 3 replications x 20 items =235440 values). The same number of values are automatically collected for inventory costs. Obviously it is out of the scope of this chapter to report all simulation results; some simulation results are reported and discussed to provide the reader with a detailed overview of the proposed approach. Table 5 consists of some simulation results for store #1 in terms of fill rate, average on hand inventory and inventory costs (only for three of twenty items). The simulation results consider all factors levels combinations keeping fixed the inventory control policy (rR1). The complete analysis consider 108 simulation runs for checking all factors levels combinations both for stores and DCs. The huge number of simulation results has required the implementation of a specific tool for supporting output analysis. To this end eM-Plant is jointly used with Microsoft Excel and Minitab. As before mentioned, at the end of each replication, simulation results are automatically stored in Excel spreadsheets. Visual Basic Macros are implemented and used for performance measures calculation. Such values are then imported in Minitab projects (opportunely set with the same design of experiments) for statistic analysis. The Microsoft Excel interface works correctly in each supply chain scenario (not only in the application example proposed). The results in terms of mean values calculated by the Microsoft Excel interface can be analyzed by using plots and charts (i.e. fill rate versus inventory policies, on hand inventory versus lead time, etc.). The use of the simulation model does not necessarily require DOE , ANOVA or any kind of statistical methodologies or software.

4.1 Simulation results analysis and input output meta-models

Table 5 reports some simulation results for store #1. Let us give a look to the fill rate: the higher is the demand intensity and variability the lower is the fill rate. Such behavior could be explained by considering a greater error in lead time demand (demand forecast over the lead time) as well as a greater number of stock outs and unsatisfied orders. A three-day lead time performs better (in terms of fill rate) than one-day lead time. In addition the higher is

the demand intensity and demand variability the lower is the average on hand inventory (see items 1, 2, 3 in table 5, remaining items show a similar behavior). The higher is the lead time the higher is the average on hand inventory. In effect the higher demand intensity causes an inventory reduction (due to the higher number or orders) whilst a five-day lead time causes high values of the lead time demand. The qualitative explanation of inventory cost seems to be more difficult because of the interaction among the different factors levels.

It is worth say that a qualitative description or analysis of simulation results does not provide a deep understanding of the supply chain behavior and could lead to erroneous conclusions in the decision making process. We know that experiments are natural part of the engineering and scientific process because they help us in understanding how systems and processes work. The validity of decisions taken after an experiment strongly depends on how the experiment was conducted and how the results were analyzed. For these reasons, we suggest to use the simulation model jointly with the Design of Experiment (DOE) and the Analysis of Variance (ANOVA): DOE for experiments planning and ANOVA for understanding how factors (input parameters) affect the supply chain behavior. In effect, many definitive simulation references (i.e. Banks, 1998) say that if some of the processes driving a simulation are random, the output data are also random and simulation runs result in estimates of performance measures. In other words, specific statistical techniques (i.e. DOE and ANOVA) could provide a good support for simulation results analysis.

Our treatment uses ANOVA for understanding the impact of factors levels on performance measures. Let Y_k be one of the performance measures previously defined (k = 1, 2, 3), let x_i be the factors or treatments (with x_i varying between the levels specified in table 4), let β_{ij} be the coefficients of the model and let hypothesize a linear statistic input-output model to express Y_k as function of x_i.

$$Y_k = \beta_{0,k} + \sum_{j=1}^{j=h} \beta_{j,k} x_{j,k} + \sum \sum_{i<j} \beta_{ij,k} x_{i,k} x_{j,k} + \sum \sum \sum_{i<j<m} \beta_{ijm,k} x_{i,k} x_{j,k} x_{m,k} +$$
$$+ \sum \sum \sum \sum_{i<j<m<n} \beta_{ijmn,k} x_{i,k} x_{j,k} x_{m,k} x_{n,k} + \varepsilon_k \tag{14}$$

k = 1, 2, 3 number of performance measures;
h = 1, 2, 3, 4 number of factors.

The Analysis of Variance allows to evaluate those factors that have a real impact on the performance measure considered or, in other words, evaluating all the terms in equation (14) eventually deleting insignificant factors from the input-output model. The Analysis of Variance decompose the total variability of Y_k into components; each component is a sum of squares associated with a specific source of variation (treatments) and it is usually called treatment sum of squares. Without enter in formulas details, if changing the levels of a factor has no effect on Y_k variance, then the expected value of the associated treatment sum of squares is just an unbiased estimator of the error variance (this is known as null hypothesis, H_0).

On the contrary, if changing the level of a factor has effect on Y_k, then the expected value of the associated treatment sum of squares is the estimation of the error plus a positive term that incorporates variation due the effect of the factor (alternative hypothesis, H_1). It follows that, by comparing the treatment mean square and the error mean square, we can understand which factors affect the performance measure Y_k. Such comparison is usually made by using a Fisher-statistic test. In addition, the ANOVA evaluates the coefficients of equation 14.

Table 5. Simulation results for Store #1 (rR1 inventory control policy, 3/20 items)

Inventory Control Policy	Lead Time	Demand Intensity	Demand Variability	Run Order	Fill Rate	Average OHI – Item1	Average OHI – Item2	Average OHI – Item3	
rR1	1	Low	Low	1	0,762	103	85	78	
rR1	1	Low	Medium	2	0,728	104	84	79	
rR1	1	Low	High	3	0,733	104	85	80	
rR1	1	Medium	Low	4	0,536	37	36	34	
rR1	1	Medium	Medium	5	0,533	38	36	35	
rR1	1	Medium	High	6	0,525	37	36	35	
rR1	1	High	Low	7	0,386	20	19	20	
rR1	1	High	Medium	8	0,385	20	18	19	
rR1	1	High	High	9	0,374	21	19	20	
rR1	3	Low	Low	10	0,838	112	95	89	
rR1	3	Low	Medium	11	0,833	113	94	90	
rR1	3	Low	High	12	0,813	113	95	90	
rR1	3	Medium	Low	13	0,578	52	49	48	
rR1	3	Medium	Medium	14	0,554	53	50	51	
rR1	3	Medium	High	15	0,560	54	48	49	
rR1	3	High	Low	16	0,402	36	34	45	
rR1	3	High	Medium	17	0,376	40	38	42	
rR1	3	High	High	18	0,379	41	42	35	
rR1	5	Low	Low	19	0,828	119	100	93	
rR1	5	Low	Medium	20	0,837	118	101	95	
rR1	5	Low	High	21	0,829	119	98	94	
rR1	5	Medium	Low	22	0,561	55	57	51	
rR1	5	Medium	Medium	23	0,581	58	56	58	
rR1	5	Medium	High	24	0,568	57	56	53	
rR1	5	High	Low	25	0,394	49	48	54	
rR1	5	High	Medium	26	0,399	54	49	51	
rR1	5	High	High	27	0,399	48	49	42	

Table 6 consists of some results obtained using the statistical software Minitab: the fill rate ANOVA (table 6, upper part) and average on hand inventory ANOVA (table 6, lower part) of item #1 for store #1. In addition, table 6 reports all the terms of equation 14 (for both performance measures).

From the ANOVA theory it is well known that all the factors with a *p* value less or equal to the confidence level used for the analysis (α=0.05) have an impact on the performance measure. The *P*-value is the probability that the F-statistic test will take on a value that is at least as extreme as the observed value of the statistic when the null hypothesis *H0* is true.

Let us discuss the results of the fill rate ANOVA reported in the upper part of table 6. Note that all factors levels have an impact on the fill rate. All the effects have to be taken into consideration: first order, second order, third order and fourth order effects. Such results show the high complexity of a supply chain and the strong interaction among the control policy used for inventory management and other critical factors such as demand intensity and variability and lead times (usually in many systems the third and fourth effects can be neglected).

For a better understanding of the fill rate analysis of variance (for store #1) we have plotted (see figures 10 and 11) the main effects and the second order interaction effects of equation (14). The inventory control policies have a different effect on store #1 fill rate. *rR1* and rR3 give as result an average fill rate of about 0.55 (mostly showing an analogous behavior); rR2gives an average fill rate of about 0.40 (the worst performance) and rR4 about 0.60 (the best one). The rR4 policy performs better than the other policies because it uses the policy parameters review period is based on cost optimization. The demand intensity has a strong impact on fill rate due to the greater number of required items: the average fill rates is about 0.80 in correspondence of low demand intensity, 0.50 in correspondence of medium intensity and 0.35 in case of high intensity. Lead times and demand variability cannot be considered as important as inventory control policy and demand intensity even if their effect on fill rate cannot be neglected.

Now let us focus on interaction effects (see fig. 11). The interaction between inventory control policies and lead times show a better behavior for rR1 and rR2 in correspondence of high lead times (the average fill rate increases in correspondence of higher lead times from 0.5 to 0.6 for rR1 policy and from 0.25 to 0.40 for rR2 policy). On the contrary, rR3 and rR4 show an opposite behavior and perform better with low lead-time values: the average fill rate decreases from 0.65 to 0.50 for rR3 policy and from 0.65 to 0.60 for rR4 policy. Note that the fill rate reduction with rR4 is smaller than the reduction with rR3. With regards to demand intensity rR1, rR3, rR4 policies show a similar trend in correspondence of low, medium and high demand intensity (the fill rate decrease from 0.90 to 0.40), whilst rR2 gives lower fill rate values (from 0.60 to 0.20). Similar results emerge when considering demand variability: rR1, rR3, rR4 policies show a similar trend (fill rate around 0.60 even if the rR4 performs better than rR1 and rR3), whilst rR2 gives the worst performance (fill rate about 0.40). All the remaining plots in figure 10 give useful information as well as help in understanding how the interaction among factors levels affect the store fill rate.

Both first order effect plots (figure 10) and interaction plots (figure 11) are obtained by using equation 14. The *Terms* columns (upper part of table 6) report all the values of the coefficients of equation 14. Such coefficients must be read per column and their order reflects the order of the experimental design matrix (i.e. consider the performance measure fill rate, Y_1, β_{01}=0.0022, β_{11}=-0.0010, etc.). Focusing only on fill rate, the best design solution for store #1 is rR4 inventory control policy and three days lead time.

Table 6. Analysis of Variance for Store #1 (*Fill Rate and item#1 Average On Hand Inventory*) and equation 14 coefficients

Fill rate ANOVA – Store #1

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Terms	Terms	Terms	Ter
x_1	3	2,87475	2,87475	0,95825	5832,04	0,000	0,7185	0,0022	-0,0054	-0,02
x_2	2	0,07717	0,07717	0,03858	234,83	0,000	0,0314	-0,0010	-0,0051	-0,00
x_3	2	11,07926	11,07926	5,53963	33714,93	0,000	-0,1575	-0,0288	0,0115	-0,01
x_4	2	0,01681	0,01681	0,00841	51,16	0,000	0,0335	-0,0158	0,0112	0,00
x_1*x_2	6	0,41302	0,41302	0,06884	418,95	0,000	-0,0192	0,0409	-0,0058	0,00
x_1*x_3	6	0,18962	0,18962	0,0316	192,34	0,000	0,0185	-0,0005	-0,0060	-0,00
x_1*x_4	6	0,03237	0,03237	0,00539	32,83	0,000	0,2402	-0,0052	0,0016	-0,00
x_2*x_3	4	0,13543	0,13543	0,03386	206,07	0,000	-0,0306	-0,0051	0,0069	0,00
x_2*x_4	4	0,0231	0,0231	0,00577	35,15	0,000	0,0057	-0,0014	-0,0040	-0,00
x_3*x_4	4	0,04209	0,04209	0,01052	64,05	0,000	0,0044	0,0096	0,0107	0,02
$x_1*x_2*x_3$	12	0,19436	0,19436	0,0162	98,58	0,000	-0,0139	0,0142	-0,0593	0,02
$x_1*x_3*x_4$	12	0,07523	0,07523	0,00627	38,16	0,000	-0,0036	-0,0309	0,0284	-0,01
$x_2*x_3*x_4$	8	0,05234	0,05234	0,00654	39,82	0,000	-0,0555	-0,0016	0,0113	-0,01
$x_1*x_2*x_4$	12	0,08415	0,08415	0,00701	42,68	0,000	-0,0005	0,0172	-0,0012	-0,00
$x_1*x_2*x_3*x_4$	24	0,16346	0,16346	0,00681	41,45	0,000	0,0460	-0,0134	0,0271	-0,00
Error	216	0,03549	0,03549	0,00016			0,0239	-0,0026	-0,0337	0,00
Total	323	15,48867					-0,0196	-0,0034	0,0091	0,00

Item #1 on hand inventory ANOVA – Store #1

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Terms	Terms	Terms	Ter
x_1	3	115183,2	115183,2	38394,4	6738,78	0,000	75,8025	1,3951	-0,3272	-0,17
x_2	2	29430,7	29430,7	14715,3	2582,76	0,000	-15,7284	3,9012	-0,4846	-0,91
x_3	2	199587,1	199587,1	99793,5	17515,22	0,000	-20,5679	1,8642	0,2469	-0,32
x_4	2	105,2	105,2	52,6	9,23	0,000	11,3333	-11,8519	0,1728	0,17
x_1*x_2	6	674,7	674,7	112,5	19,74	0,000	-12,5617	3,1481	-0,3642	0,82
x_1*x_3	6	10050,3	10050,3	1675	293,99	0,000	2,0494	0,4321	-0,1605	-0,82
x_1*x_4	6	138,8	138,8	23,1	4,06	0,001	34,8642	-0,1327	-0,4506	-0,30
x_2*x_3	4	2924,1	2924,1	731	128,31	0,000	-13,9136	-0,2840	0,3920	0,37
x_2*x_4	4	92,2	92,2	23,1	4,05	0,003	-0,8025	-0,5525	-0,9043	0,50
x_3*x_4	4	26,1	26,1	6,5	1,15	0,336	0,4660	0,3704	0,0216	2,81
$x_1*x_2*x_3$	12	995,3	995,3	82,9	14,56	0,000	-0,1420	0,9537	-1,3642	0,81
$x_1*x_3*x_4$	12	426,2	426,2	35,5	6,23	0,000	0,7284	4,3395	-0,0772	-1,01
$x_2*x_3*x_4$	8	236,3	236,3	29,5	5,18	0,000	3,0309	0,4228	-0,7809	-1,07
$x_1*x_2*x_4$	12	469,9	469,9	39,2	6,87	0,000	-1,1358	-0,2438	0,4784	-0,33
$x_1*x_2*x_3*x_4$	24	786,6	786,6	32,8	5,75	0,000	-0,5741	0,2006	3,5370	-0,54
Error	216	1230,7	1230,7	5,7			-0,5556	0,2006	-1,3241	0,79
Total	323	362357,4					2,0988	-0,2901	2,1574	0,48

Let us consider now the analysis of variance of the average on hand inventory for store #1 and item #1 (lower part of table 6). All the factors have an impact on the average on hand inventory except for the interaction x3*x4 (Demand Intensity and Demand Variability). The lower right part of table 6 consists of terms of equation (14). Also in this case the equation 14 can be used for plotting first order and interaction effects and understanding, from a quantitative point of view, the average on hand inventory behavior.

Needless to say that similar results have been obtained for the third performance measure, the inventory cost. The same approach is followed for each item of store #1, for each store and for each distribution center. Note that the aim of the application example is not to find out the best configuration of the supply chain but to show the complexity of the inventory problem along the supply chain and the simulation potentials as decision-making tool for supply chain management. The high level of results detail (analysis of the fill rate for each supply chain node, analysis of on hand inventory and inventory costs for each item and in each supply node) helps in understanding simulation models capabilities as decision-making tool. In effect as reported in literature (refer to literature overview section) the supply chain decision process requires accurate analysis on the whole supply chain. In addition, the simulation model architecture jointly with Excel and Minitab spreadsheets guarantees high flexibility in terms of supply chain scenarios definition, high efficiency in terms of time for executing simulation runs and analyzing simulation results.
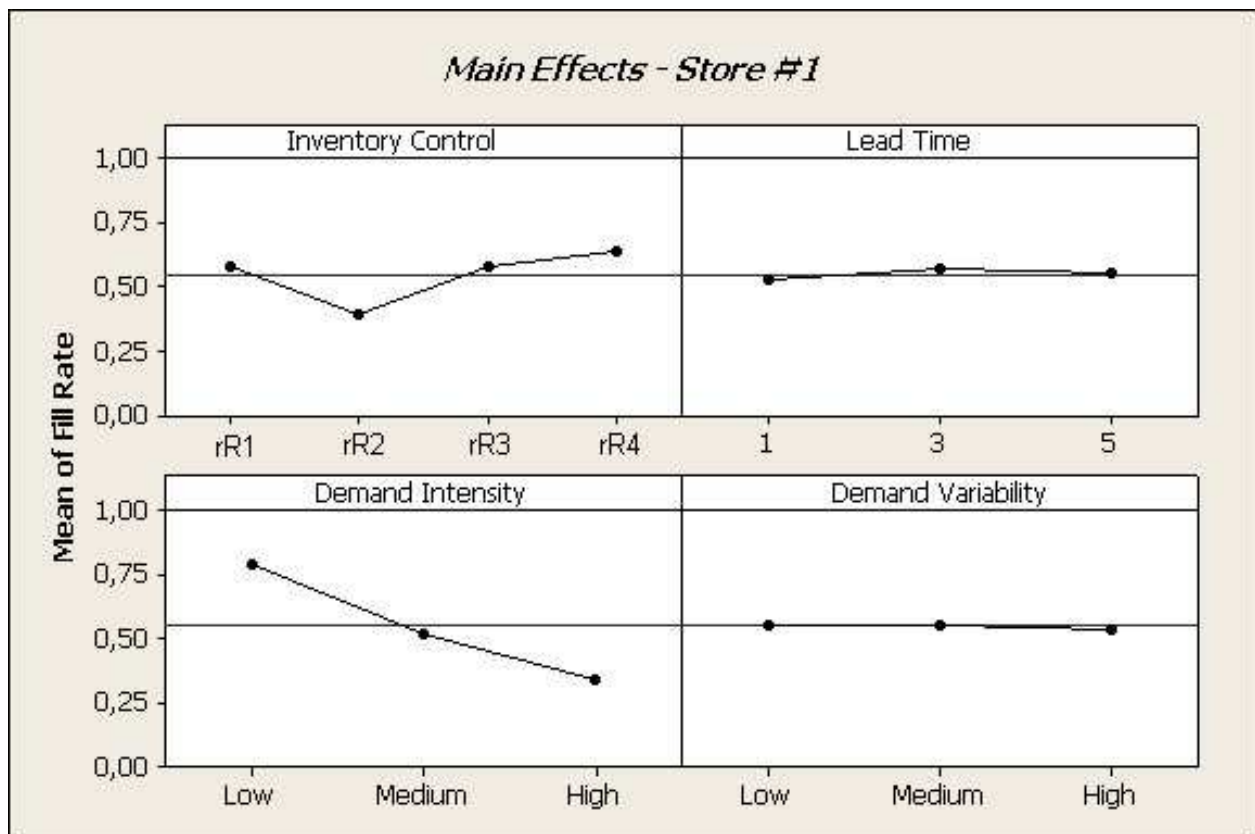

Fig. 10. Main effects plot: Store #1 fill rate versus inventory control policies, lead time, demand intensity and demand variability
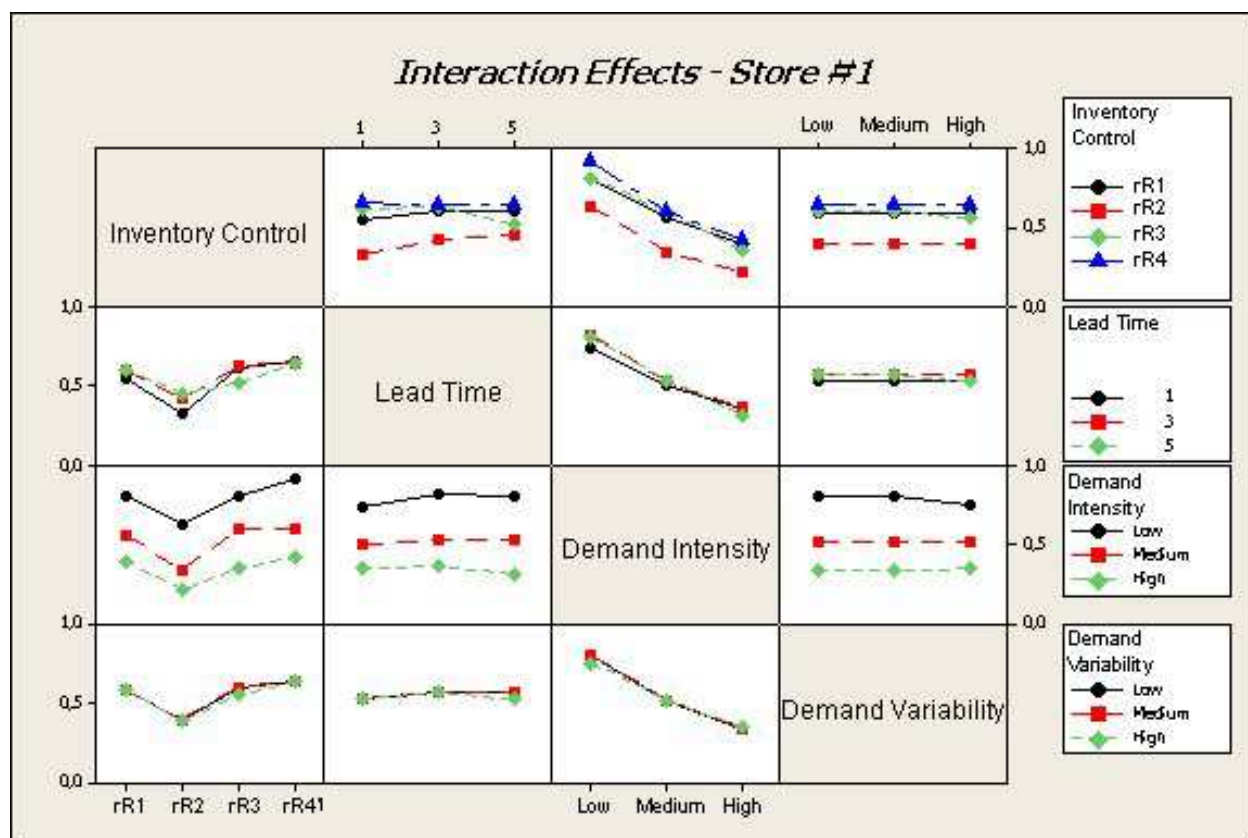
Supply Chain Management Based on Modeling & Simulation: State of the Art and
Application Examples in Inventory and Warehouse Management
123

Fig. 11. Effects of factors interaction on fill rate

4.2 Testing the simulation results validity: residuals analysis

In using ANOVA for simulation results analysis, we strongly suggest to test ANOVA results validity. The Analysis of Variance assumes (as starting hypothesis) that the observations are normally and independently distributed, with the same variance for any combination of factors levels. These assumptions must be verified by means of the analysis of residuals for accepting the validity of the input-output analytical models (equation 14).

A residual is the difference between an observation of the performance measure and the corresponding average value calculated on the 3 replications. The assumption of normality can be tested by building a *normal probability plot* of residuals. If residuals approximately fall along a straight line passing form the centre of the graph, the assumption of normality can be accepted. In figure 12 (upper-left part) we observe that the deviation from normality is not severe (store #1, fill rate). The assumption of equal variance is tested by plotting residuals against the factors levels or against the fill rate: residuals variability must anyhow not depend on the level of factors or on the fill rate. Figure 12 (upper-right part) shows residuals versus the fitted values and do not show any particular trend; therefore, the equal variance hypothesis is accepted. Finally, the assumption of independence is tested by plotting residuals against the implementation order of simulation runs. A sequence of positive or negative residuals could indicate that observations are dependent among themselves. Figure 12 (lower part) shows that the hypothesis of independence of observations is accepted. The residuals analysis, as part of the Minitab standard tools, can be easily carried out for each supply chain scenario.

In case of starting hypothesis rejection, a linear statistical model (as the model in equation 14) must be rejected. A test for model curvature should be conducted.
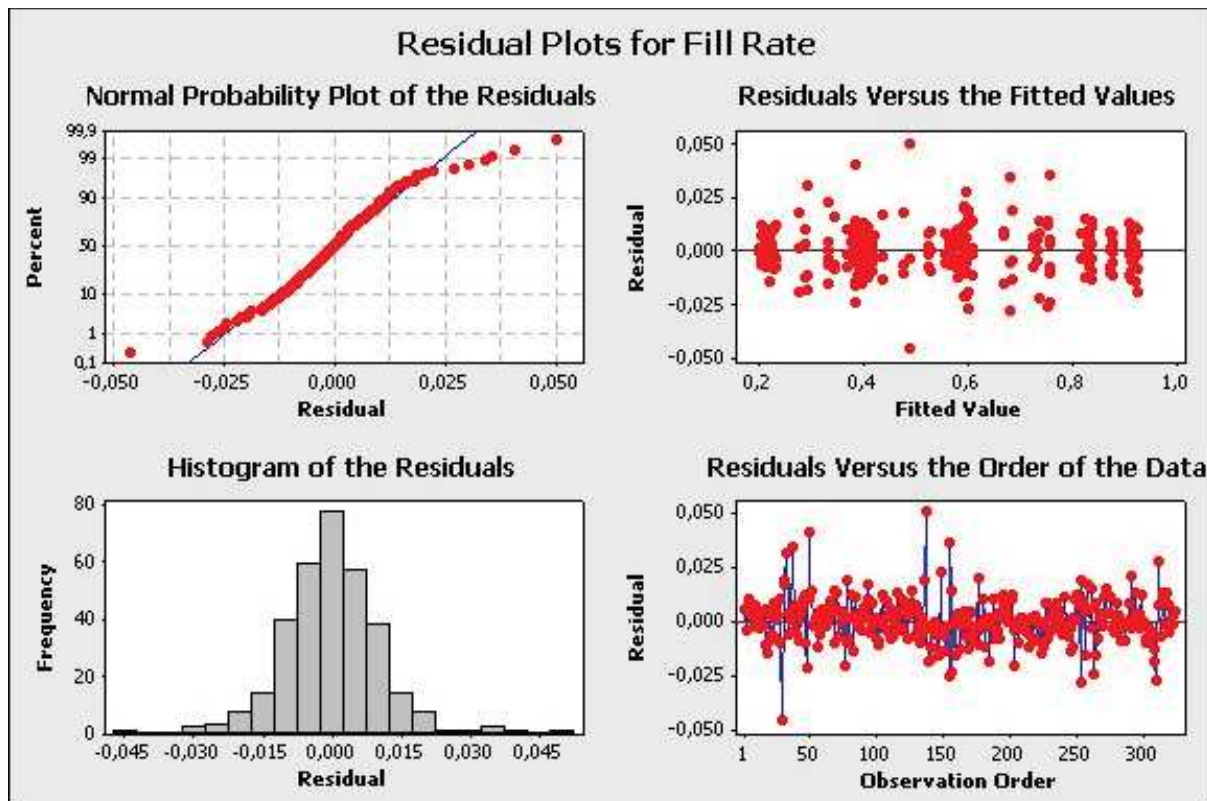
Fig. 12. Test of the simulation results validity: Residuals analysis

5. The Warehouse management problem: interactions among operational strategies, available resources and internal logistic costs

The survey of state of art proposed in section 2.2 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). The application example proposed in this section investigates the effects of warehouse resources management on warehouse efficiency highlighting as the interactions among operational strategies and available resources strongly affect the internal logistic costs. In particular the simulation model of a real warehouse is presented. 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.

5.1 Warehouse description and warehouse simulation model

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

- total surface: 13000 m²;
- shelves surface: 5000 m²;
- surface for packing and shipping operations: 3000 m²;
- surface for unloading and control operations: 1800 m²;
- three levels of shelves;
- eight types of products;
- capacity in terms of pallets: 28400 pallets;

- capacity in terms of pallets for each product: 3550 pallets;
- capacity in terms of packages: about one million packages.

Figure 13 shows the warehouse layout.

Fig. 13. The warehouse layout

The main modeling effort was carried out to recreate with satisfactory accuracy the most important warehouse operations:

- trucks arrival and departure for items deliveries (from suppliers to the warehouse and from the warehouse to retailers);
- materials handling operations (performed by using forklifts and lift trucks) including, trucks unloading operations, inbound quality and quantity controls, preparation for storage, storage operations, retrieval operations, picking operations, preparation for shipping, packaging operations, trucks loading operations and shipping;
- performance measures control and monitoring (a detailed description of performance measures will be provided later on).

The simulation software adopted for developing WILMA simulator is the commercial package Anylogic™ by *XJ Technologies*. Most of the logics and rules of the real warehouse are implemented by using ad-hoc Java routines. The description proposed below will be useful for those readers interested in developing similar simulation models. Figure 14 shows the simulation model Flow Chart.

In order to support scenarios investigation, the main variables of the WILMA simulator have been completely parametrized. To this end, the simulator is equipped with 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*).
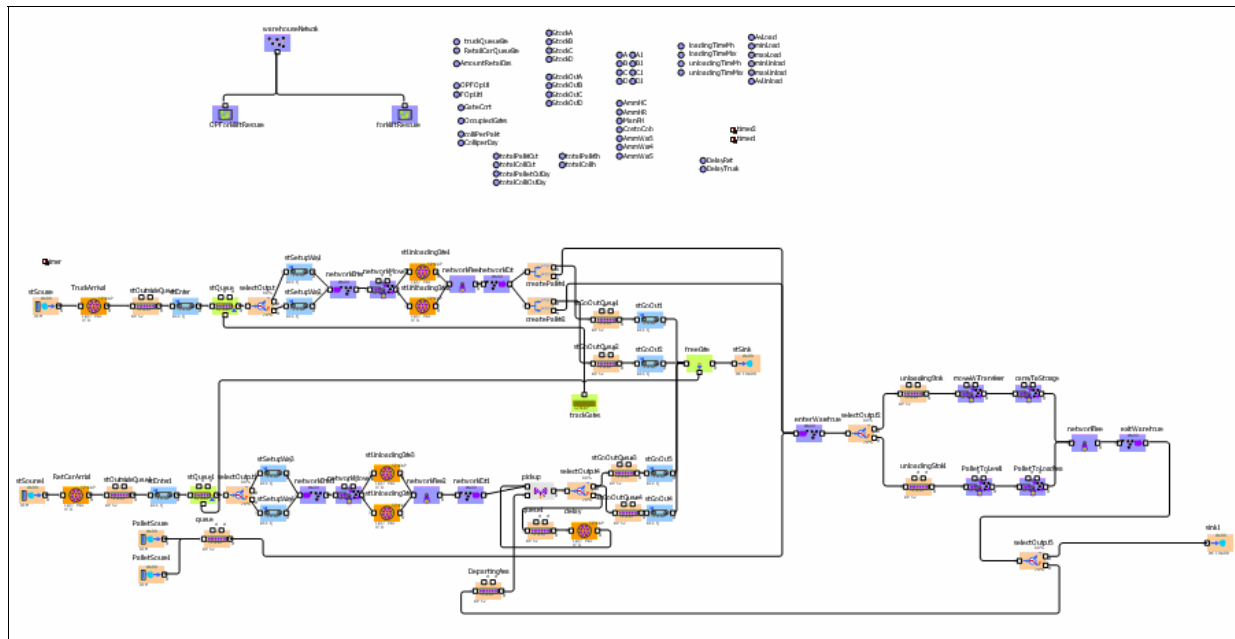
Fig. 14. The WILMA Simulation Model Flow Chart

The *Input Section* (figure 15) is in four different parts:

- The *Suppliers' Trucks* section which includes slider objects for changing 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 includes slider objects for changing the following parameters: retailers' trucks arrival time, number of retailers' trucks per day, time window for retailers' trucks arrival, time for starting items preparation;

Fig. 15. The WILMA Input Section (part of the WILMA Graphic User Interface)

- the *Warehouse Management parameters* section which includes slider objects for changing the following parameters: shelves levels, number of forklifts, number of lift trucks, number of docks available for loading and unloading operations, forklifts and lift trucks efficiency, stock-out costs parameters;
- the *Logistics Internal Costs* section which includes slider objects for changing the following parameters: sanction fee for retailers/suppliers, time after which the warehouse has to pay a sanction fee to retailers for operations performed out of the scheduled period, time after which suppliers have to pay a sanction fee to the warehouse for operations performed out of the scheduled period.

The *Output Section* (figure 16) provides the user with the most important warehouse performance measures. The main performance measures include the following:

- 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);
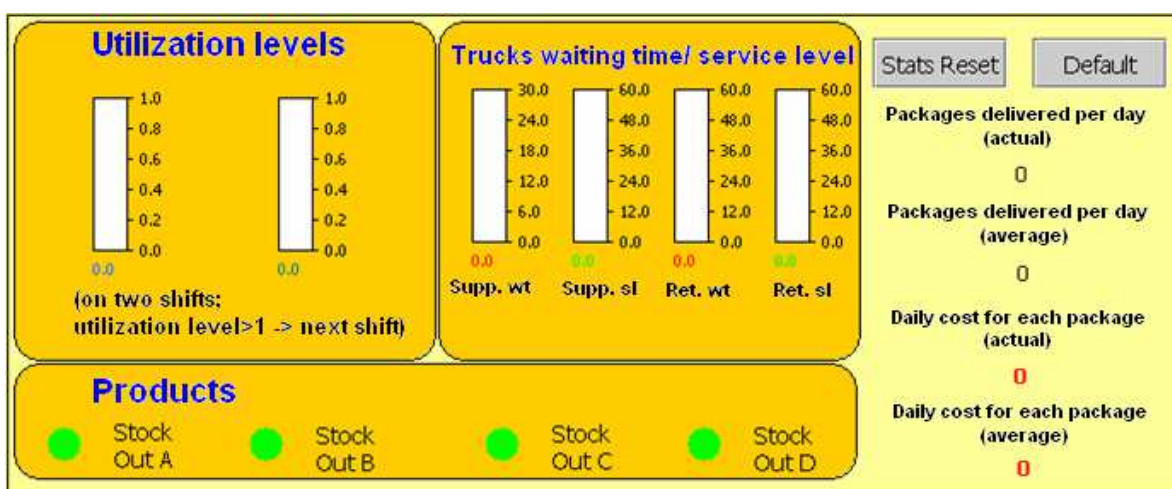- daily cost for each handled package (actual and average values).

Fig. 16. The WILMA Output Section (part of the WILMA Graphic User Interface)

5.2 Internal logistics management: scenarios definition and simulation experiments

The WILMA simulation model has been used to investigate the effects of warehouse resources management on warehouse efficiency highlighting as the interactions among operational strategies and available resources strongly affect the internal logistic costs. The analysis carried out by using the WILMA simulator include the following:

- internal resources allocations versus number of packages handled per day;
- internal resources allocations versus the daily cost for each handled package;
- Internal resources allocations versus suppliers' waiting time and retailers' waiting time

In each case a sensitivity analysis is carried out and an input-output analytical model is determined. As in the first application example, the simulation approach is jointly used with the Design of Experiments and Analysis of Variance.

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 operative strategies and resources availability, allocation and utilization. The performance measures considered are:
- the average number 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 (a Full Factorial Experimental Design is used). Table 7 consists of factors and levels used for the design of experiments.

Factors	Level 1	Level 2
Number of suppliers' trucks per day, *NTS* (x_1)	80	100
Number of retailers' trucks per day, *NTR* (x_2)	30	40
Number of forklifts, *NFT*, (x_3)	6	24
Number of lift trucks, *NMT*, (x_4)	12	50
Number of shelves levels, *SL*, (x_5)	3	5

Table 7. DOE Factors and Levels

As shown in Table 7, 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 is replicated three times, so the total number of replications is 96 (32x3=96). The simulation results are studied, according to the various experiments, by means of the Analysis Of Variance (*ANOVA*) and graphic tools.

Let Y_i be the i-th performance measure and let x_i be the factors, equation 15 expresses the i-th performance measure as linear function of the factors.

$$Y_i = \beta_0 + \sum_{i=1}^{5} \beta_i x_i + \sum_{i=1}^{5}\sum_{j>i}^{5} \beta_{ij} x_i x_j + \sum_{i=1}^{5}\sum_{j>i}^{5}\sum_{h>j}^{5} \beta_{ijh} x_i x_j x_h + \sum_{i=1}^{5}\sum_{j>i}^{5}\sum_{h>j}^{5}\sum_{k>h}^{5} \beta_{ijhk} x_i x_j x_h x_k +$$
$$+\sum_{i=1}^{5}\sum_{j>i}^{5}\sum_{h>j}^{5}\sum_{k>h}^{5}\sum_{p>k}^{5} \beta_{ijhkp} x_i x_j x_h x_k x_p +\varepsilon_{ijhkpn} \tag{15}$$

where:

β_0 is a constant parameter common to all treatments;

$$\sum_{i=1}^{5} \beta_i x_i \text{ are the five main effects of factors;}$$

$$\sum_{i=1}^{5} \sum_{j>i}^{5} \beta_{ij} x_i x_j \text{ are the ten two-factors interactions;}$$

$$\sum_{i=1}^{5} \sum_{j>i}^{5} \sum_{h>j}^{5} \beta_{ijh} x_i x_j x_h \text{ represents the three-factors interactions;}$$

$$\sum_{i=1}^{5} \sum_{j>i}^{5} \sum_{h>j}^{5} \sum_{k>h}^{5} \beta_{ijhk} x_i x_j x_h x_k \text{ are the three four-factors interactions;}$$

$$\sum_{i=1}^{5} \sum_{j>i}^{5} \sum_{h>j}^{5} \sum_{k>h}^{5} \sum_{p>k}^{5} \beta_{ijhkp} x_i x_j x_h x_k x_p \text{ is the sole five-factors interaction;}$$

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.

5.3 Internal resources allocations versus number of packages handled per day (*APDD*)

Table 8 reports the experiments design matrix and the simulation results in terms of average number of handled packages per day. The first four 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 8 are values obtained as average on three simulation replications.

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 measure) and α = 0.05 is the confidence level used in the analysis of variance. According to the ANOVA, 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).

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 8. Design Matrix and Simulation Results (APDD)

ANOVA results are summarized in table 9:
- the first column reports the sources of variations;
- the second column is the degree of freedom (*DOF*);
- the third column is the 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	DOF	AdjSS	AdjMS	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 9. ANOVA Results for APDD (most significant factors)

Supply Chain Management Based on Modeling & Simulation: State of the Art and
Application Examples in Inventory and Warehouse Management
131

The input-output meta-model expressing APDD as function of the most important factors is the following:

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

(16)

Equation 16 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.

5.4 Internal resources allocations versus the daily cost for each handled package (*ADCP*)

The same analysis is carried out taking into consideration the average daily cost per handled packages (*ADCP*). Table 10 reports the design matrix and the simulation results. The normal

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 10. Design Matrix and Simulation Results (ADCP)

probability plot in Figure 17 allows to evaluate the predominant effects (red squares): in this case 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);
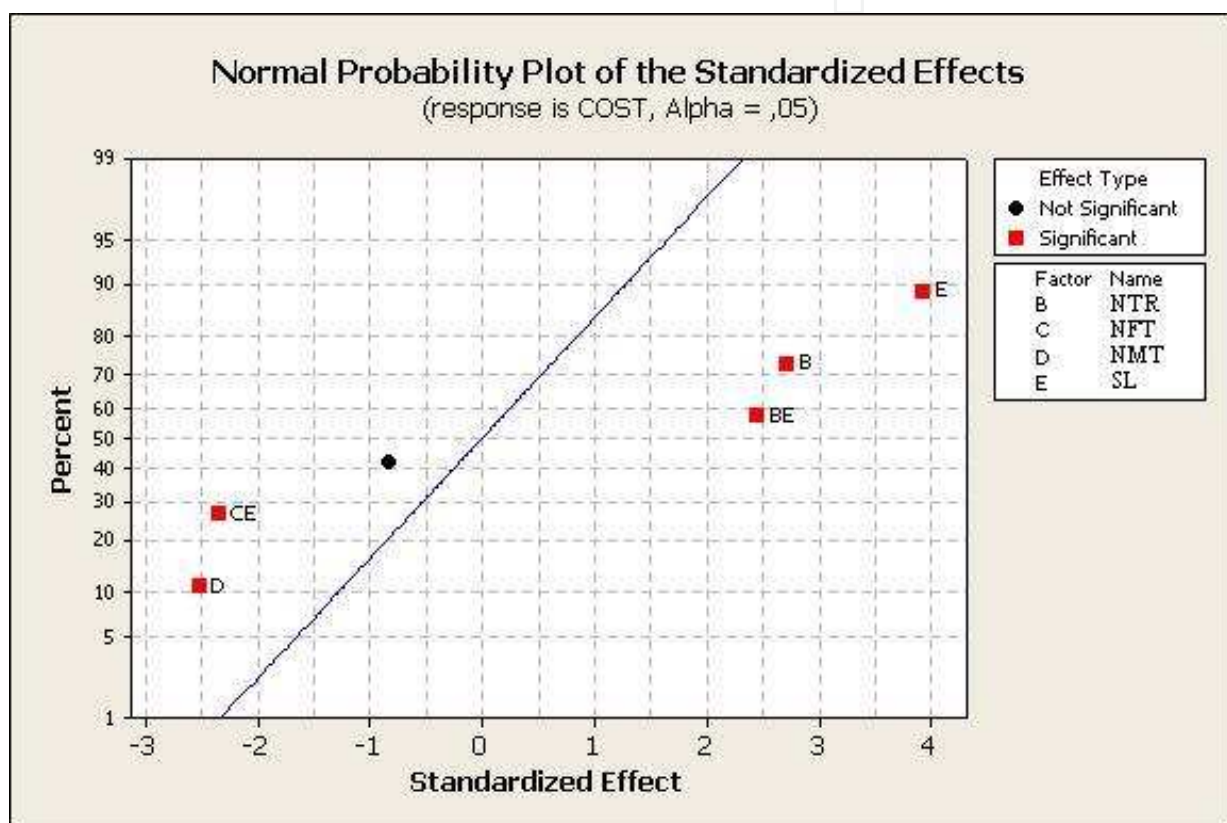- NTR*SL (the interaction between the number of retailers' trucks per day and the number of shelves levels);
- NFT*SL (the interaction between the number of suppliers' trucks per day and the number of shelves levels).

Fig. 17. The Most Significant Effects for the ADCP

Figure 18 shows the trend of ADCP in function of the main effects NTR, NMT and SL. As reported in Figure 18, 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 19 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 arrange 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 both the number of handled packages per day and the total logistic costs.
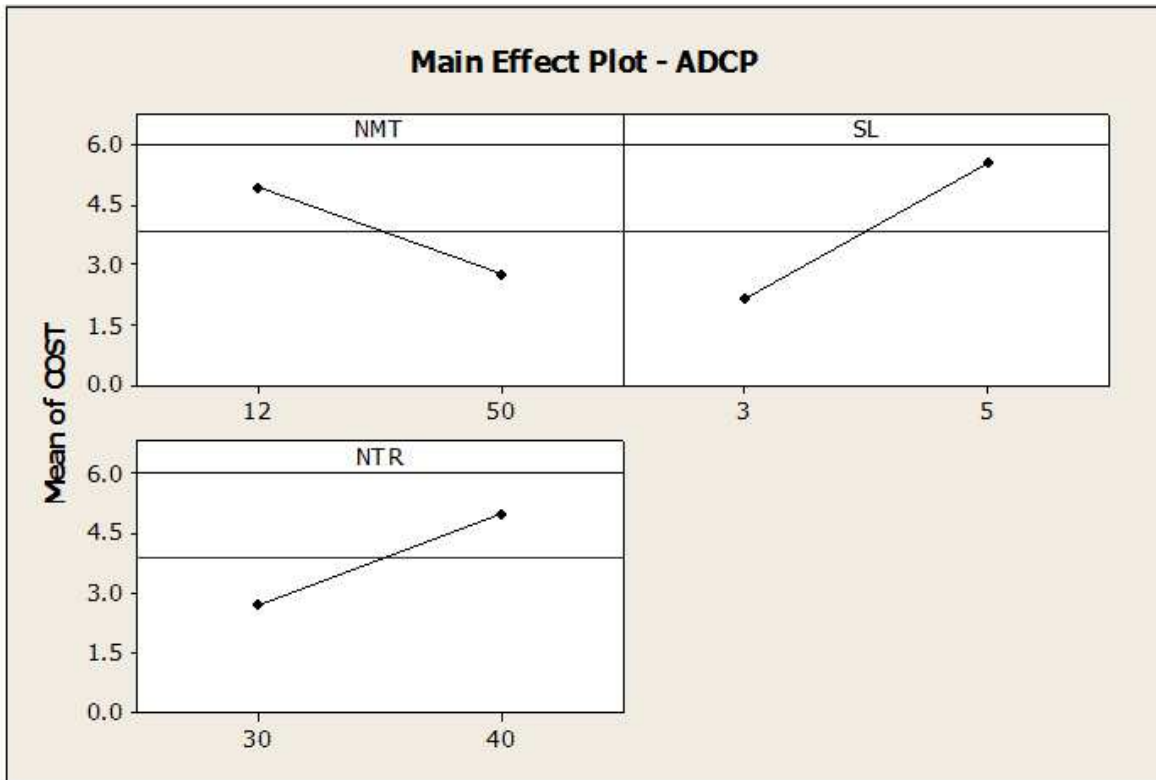
Fig. 18. ADCP versus Main Effects
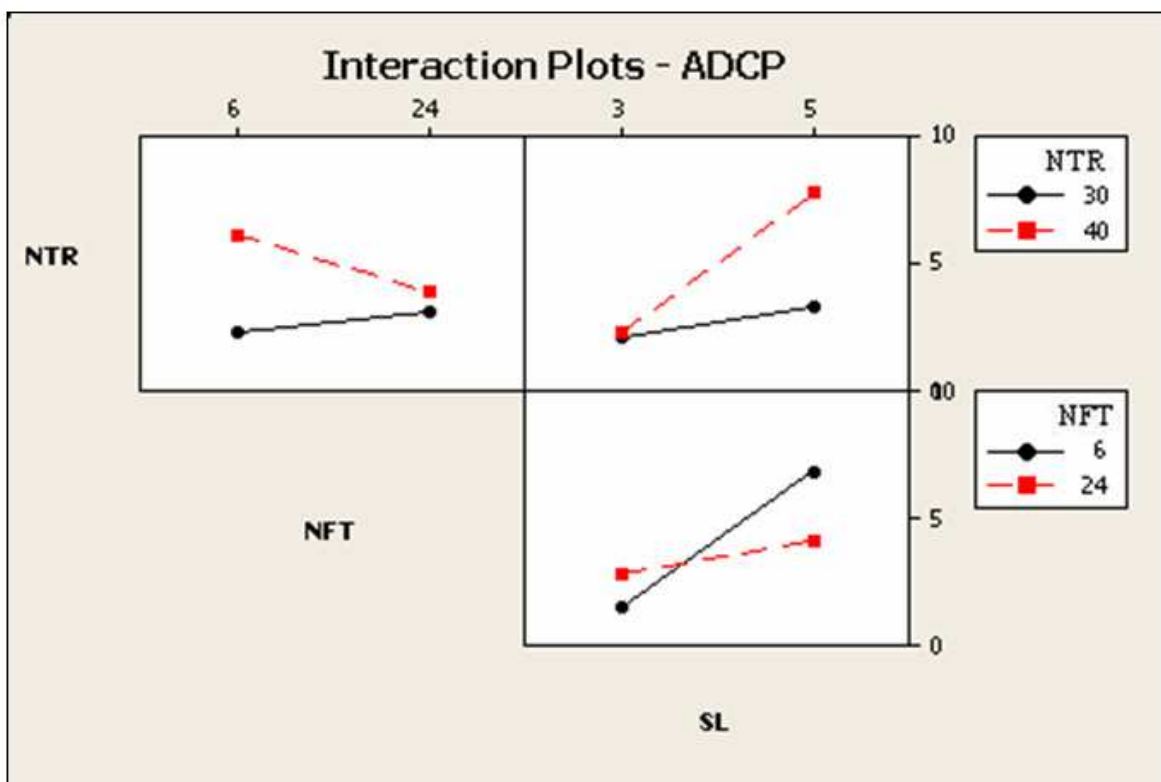
Fig. 19. Interactions Plots for the ADCP

5.5 Internal resources allocations versus suppliers' waiting time (STWT) and retailers' waiting time (RTWT)

This Section focuses on evaluating the analytical relationship between factors defined in Table 7 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.

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 α = 0.05, the Pareto Chart in Figure 20 highlights factors that influence 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*).
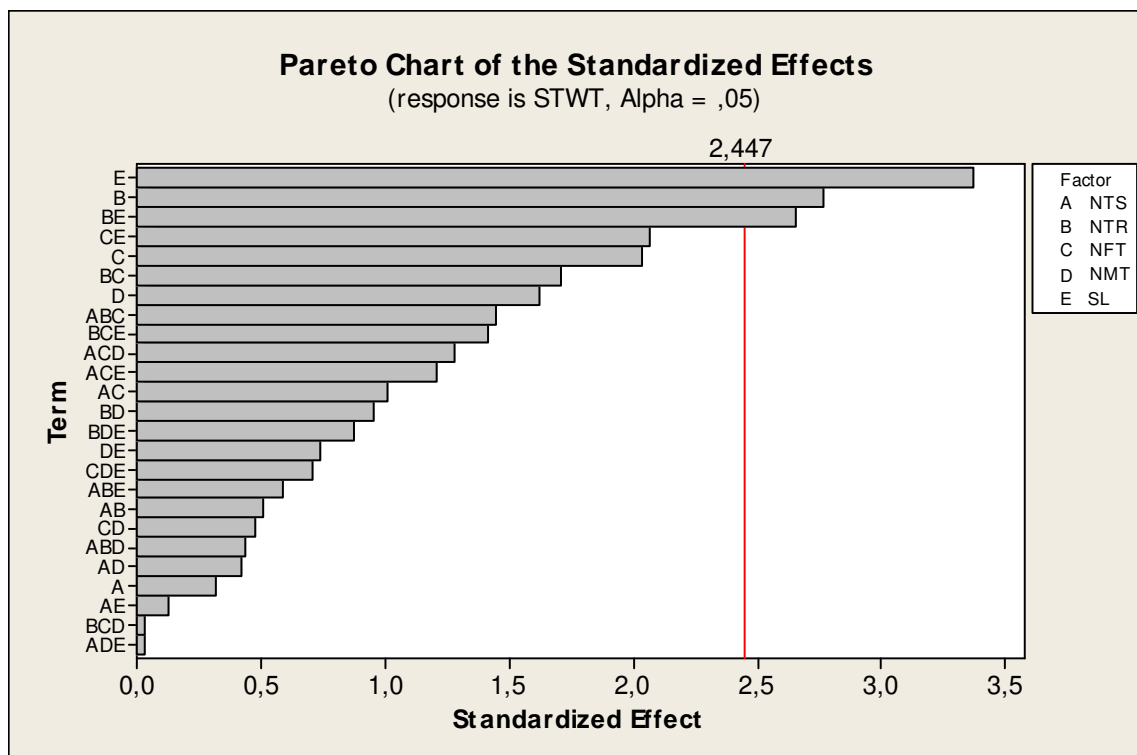
Fig. 20. The Pareto Chart for the STWT

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, as reported in Table 4.V.

Source	*DF*	*AdjSS*	*AdjMS*	*F*	*P*
Main Effects	2	14,38	7,19	8,26	0,002
2-Way interactions	1	5,34	5,34	6,14	0,02
Residual Error	28	24,39	0,871		
Total	31				

Table 11. ANOVA Results for STWT

The input-output meta-model which expresses the analytical relationship between the STWT and the most significant factors is reported in equation 17.

Supply Chain Management Based on Modeling & Simulation: State of the Art and
Application Examples in Inventory and Warehouse Management

135

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

This equation clearly explains how the waiting time of suppliers' trucks before starting the unloading operations depends on warehouse available resources.

The same analysis has been carried out taking into consideration the waiting time of retailers' trucks before starting loading operations (*RTWT*). Figure 21 (Normal Probability Plot of the Standardized Effects) helps in understanding those factors that have a significant impact on RTWT; in this case 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 12 reports analysis of variance results while equation 18 is the input-output analytical model that expresses RTWT as function of the predominant effects:

$$RTWT = 261,843 - 13,125 * NTR + 3,159 * NMT - 166,299 * SL + 0,081 * (NTS * NTR) +$$
$$-0,029 * (NTS * NFT) + 5,930 * (NTR * SL) + 0,122 * (NFT * NMT) + 1,027 * (NFT * SL) + \tag{18}$$
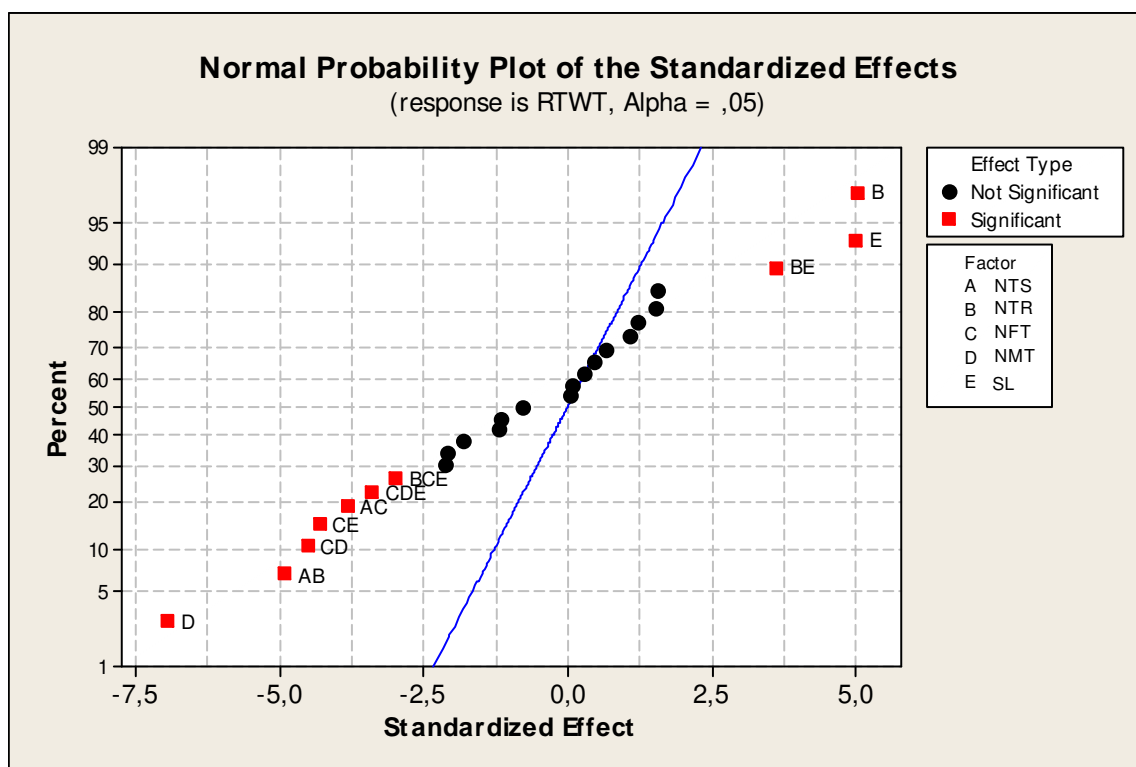$$-0,073 * (NTR * NFT * SL) - 0,022 * (NFT * NMT * SL)$$

Fig. 21. The Normal Probability Plot for the RTWT

Source	DF	AdjSS	AdjMS	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		

Table 12. ANOVA Results for RTWT

Figure 22 plots equation 18 in terms of main effects: each plot provides additional information about the effects of the most significant factors on the waiting time of retailers' trucks before starting loading operations.

Consider 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.
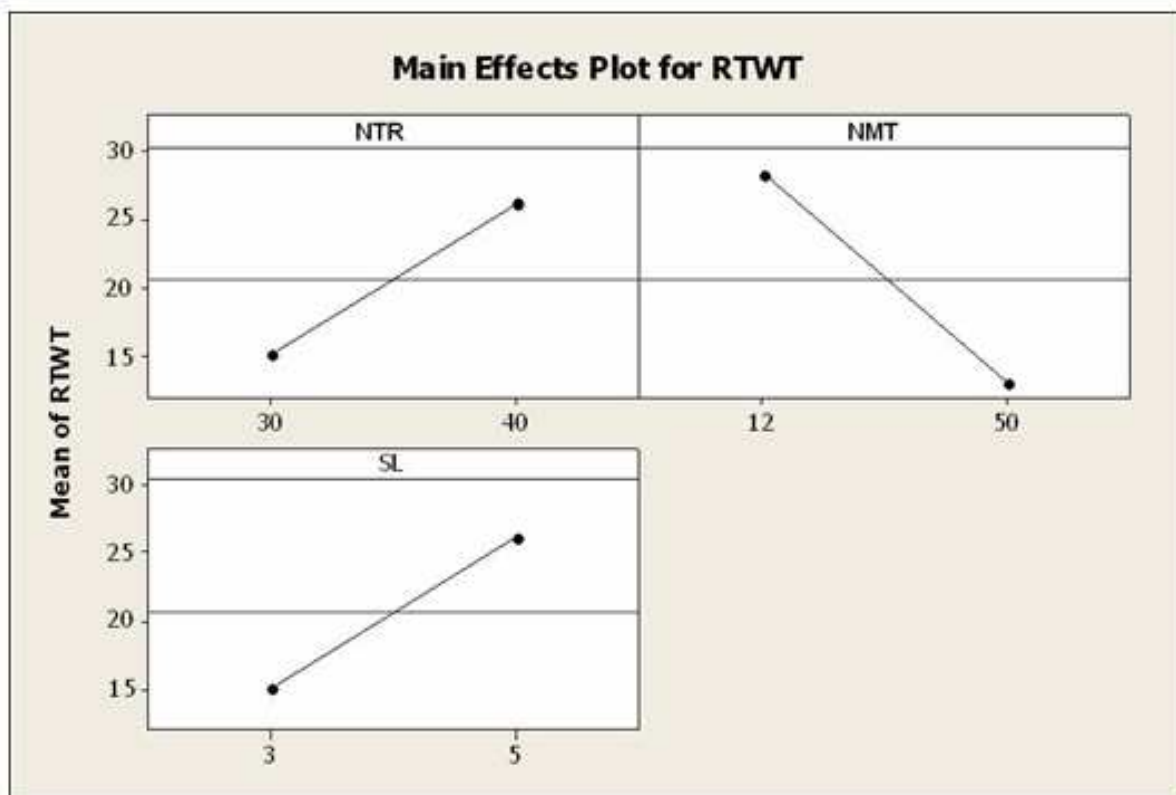
Fig. 22. Main Effects Plots for RTWT

Figure 23 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: NMT at its high value and NTR and SL at their low values are the best choice to obtain the lowest RTWT value.
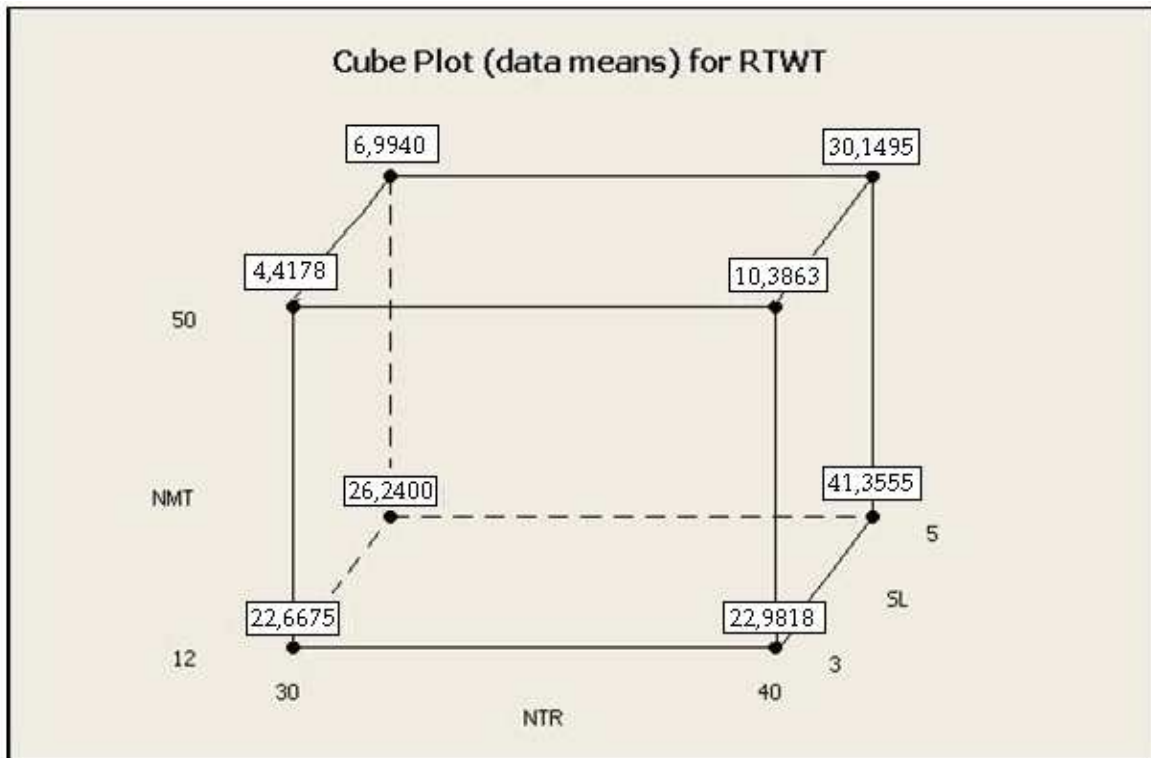
Fig. 23. Cube Plot for RTWT

Additional insights are provided by figure 24 that shows the three-dimensional surfaces of
the RTWT in function of the different combinations of significant factors (NTR, SL, NMT).
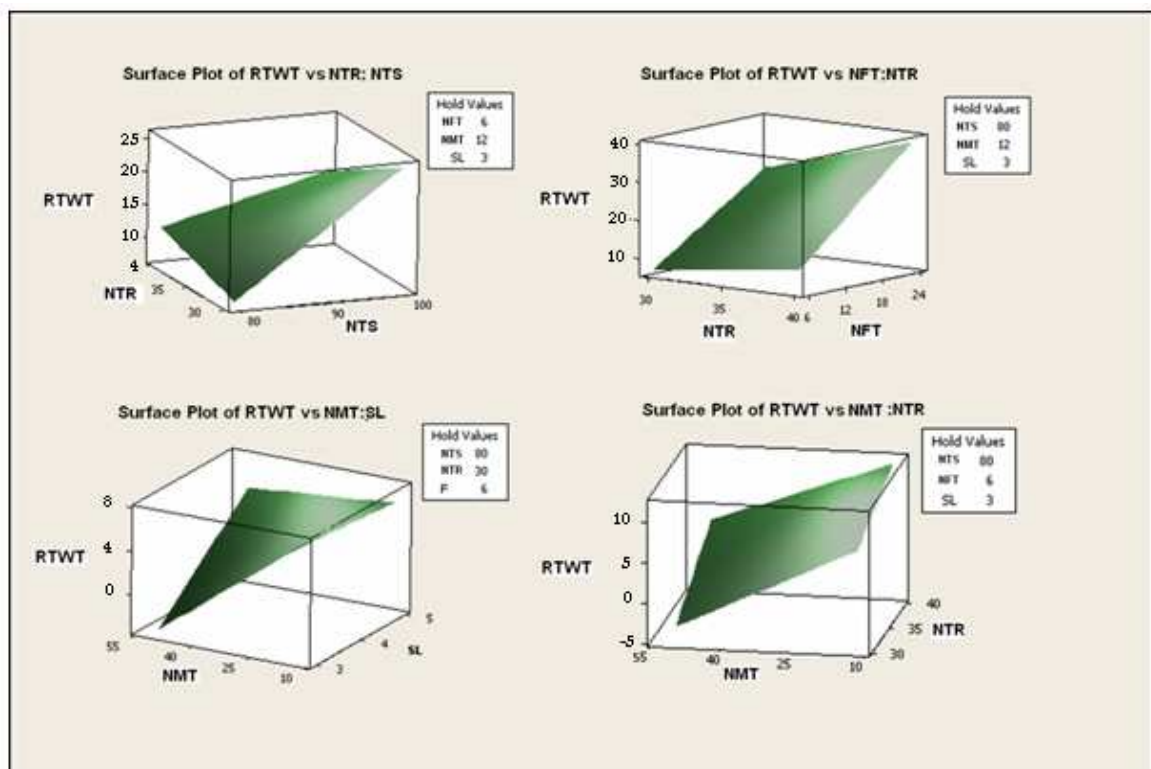

Fig. 24. Response Surfaces for RTWT

The analysis presented above show how Modeling & Simulation can be used for developing tailored solutions and tools for warehouse design and management. Input-Output analytical models and graphical tools allow to understand how changes in internal resources availability and operative strategies can affect technical and economic warehouse performances.

6. Conclusions

In this chapter the use of Modeling & Simulation as enabling technology is investigated, highlighting the contribution of this approach in supply chain management (with a specific focus on supply chain inventory and warehouse management). The literature in these two specific fields is surveyed and discussed highlighting approaches and solutions proposed during the years as well as lacks in research studies and critical issues still to be investigated.

Two application examples (based on real case studies) are then proposed. The application examples deal with advanced modeling approaches and simulation models for investigating the inventory management problem along the supply chain and the warehouse management problem within a single supply chain node. In both the application examples, simulators are decision-making tools capable of analyzing different scenarios by using approaches based on multiple performance measures and user-defined set of input parameters.

Lessons learned include operative procedures for developing supply chain simulation models, modus operandi for facing both the inventory and the warehouse management problem by using simulation for developing tailored solutions, joint use of simulation and advanced statistics techniques (DOE and ANOVA), limits and critical issues when using commercial simulation software as well as practical suggestions to overcome them.

It is not the intent of this chapter to investigate all the problems related to the inventory and warehouse management as well as to present all possible solutions. Indeed the literature review and the application examples should help the reader in understanding how Modeling & Simulation can be profitably used for recreating supply chains complexity and tackle specific problems with ad-hoc solutions.

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Supply Chain Management Based on Modeling & Simulation: State of the Art and
Application Examples in Inventory and Warehouse Management

139

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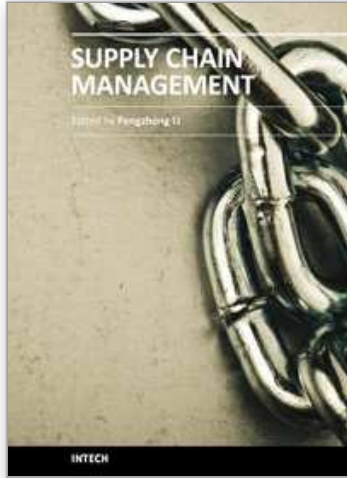
Supply Chain Management

Edited by Dr. pengzhong Li

The purpose of supply chain management is to make production system manage production process, improve customer satisfaction and reduce total work cost. With indubitable significance, supply chain management attracts extensive attention from businesses and academic scholars. Many important research findings and results had been achieved. Research work of supply chain management involves all activities and processes including planning, coordination, operation, control and optimization of the whole supply chain system. This book presents a collection of recent contributions of new methods and innovative ideas from the worldwide researchers. It is aimed at providing a helpful reference of new ideas, original results and practical experiences regarding this highly up-to-date field for researchers, scientists, engineers and students interested in supply chain management.

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