

# An Agent-based System for Sales and Operations Planning in Manufacturing Supply Chains

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*Abstract:* - A major problem faced by manufacturing organizations is providing efficient and cost-effective responses to the unpredictable changes taking place in global markets and in supply chains. Sales and Operations Planning helps giving better customer service, lower inventory, shorten customer lead times, stabilized production rates providing top management with a handle on the business and supporting a company to get and keep demand and supply in balance over time. This paper proposes a multi-agent based system that would enable small and medium-size manufacturing organizations to dynamically achieve cost-effective aggregate sales and operations plans in supply chain contexts. The simulation of the agent's interactions supports planners, in supply chain operations planning, providing multiple scenarios with respect to the balance between supply and demand. This paper presents the main features of the proposed system and it finally discusses the benefits and limitations highlighted by its application in real industrial contexts.

*Key-Words:* - Supply Chain Operations Planning; Decision Support System; Scenario Based Analysis; Multi-Agent System.

## 1 Introduction

Sales and Operations Planning (SOP) is a process to help giving better customer service, lower inventory, shorten customer lead times, stabilized production rates, and to give top management a handle on the business. According to several authors [1], the process is designed to support a company get demand and supply in balance and to keep them in balance over time putting the operational plan in line with the business plan. This balance must occur both at an aggregate level, i.e., at the level of major groups of products, and at the detailed individual product level. In addition, the available total capacity must never be exceeded over time. Since the demand is dynamic, it is important monitoring the expected needs from 3 to 18 months or further in the future. A typical corporate plan contains a section on manufacturing that specifies how many item units must be produced in each major product line over the next 12 months to meet the sales forecast. Provided that the organization has enough aggregate capacity, the individual product planners determine the weekly launching of individual product orders to meet medium and short-term demand taking into account aggregate capacity constraints and costs. Four costs can be considered as relevant.

1. Basic production costs. These are the fixed and variable costs incurred in producing a given product type in a given time period, including direct and indirect labor costs and regular as well as overtime compensation.
2. Costs associated with changes in the production rate. Typical costs in this category are those involved in hiring, training, and laying off personnel.
3. Inventory holding costs. A major component is the cost of capital tied up in inventory.
4. Backordering costs. Usually these are very hard to measure including costs of expediting, loss of customer goodwill, and loss of sales revenues resulting from backordering.

This paper contributes to the presentation of a system for Supply Chain Operations Planning (SCOP) in capacity constrained contexts. Positioning SCOP in the context of Supply Chain Management, the objective of SCOP is to coordinate the release of materials and resources in the supply network under consideration such that customer service constraints are met at minimal costs. The SCOP problem thus relates to the integration of the Master Production Schedule (MPS), Rough Cut

Capacity Planning (RCCP), Material Requirements Planning (MRP-I), and Capacity Requirements Planning (CRP) functions in the well-known MRP-II framework [2]. The main purpose of the system is to identify aggregate plans, i.e. the so-called Master Production Schedule (MPS), specifying the optimal combination of production rate, resource capacity, inventory on hand, and backordering costs [3]. The MPS is then used to feed the master-planning phases, i.e., both Material Requirement Planning / Capacity Resource Planning (MRP/CRP) and Available To Promise / Capable To Promise (ATP/CTP) modules. Even though the aforementioned phases could be accomplished manually, the time required to elaborate several alternative scenarios is considerable. Furthermore, changes in delivery plans or urgent orders require a rapid partial or total regeneration of mid-term plans in order to react timely to customer demands and production operations management. Supply and demand balance seeks solutions through the integration, optimization and alignment of operations across the entire SC at the enterprise level [3]. Unfortunately, the complexity level increases as the number of nodes in the SC increases, becoming soon uncontrollable, at least for human decision makers. Supply Chain Management (SCM) systems address these issues integrating Enterprise Resource Planning (ERP) systems and Manufacturing Execution Systems (MES). In recent years, ERP systems have been implemented in many manufacturing firms [4]. Several companies selling ERP packages now include optimization facilities based on powerful operational research approaches to help improving the quality of operations planning and scheduling [5]. Prominent examples include SAP's Advanced Production Optimizer and i2's Trade Matrix software as well as companies specialized in the provision of Advanced Planning System (APS) software, such as OPL Studio [6], which incorporates powerful modeling and optimization tools. However, these optimizers are usually expensive and need sophisticated ERP platforms to work on. These requirements are not suitable for a large number of small and medium enterprises (SME), aiming at facing Supply Chain Management (SCM) issues. The Supply Chain Operations Planning (SCOP) system presented in this paper has been designed and developed through the collaboration with an Italian software vendor of Advanced Planning Systems (APS) to harness the strengths of multi-agent systems, in order to provide SME with an efficient and easy to implement SCOP system. The rest of the paper is organized as follow. Section 2 introduces a introduction to the use of

multi-agent systems in supply-chains. Section 3 contains a formal description of the considered SCOP problem. Section 4 describes the proposed approach, and Section 5 provides a general discussion of its application in real life manufacturing contexts. Finally, Section 6 draws some conclusions.

## 2 Multi-agent systems in supply-chain management

The agile manufacturing paradigm aims at providing manufacturers with methodologies and systems to rapidly and cost-effectively respond to changes taking place in the manufacturing environment [7]. The agile manufacturing reconfiguration requires simple to use but effective information management systems to operate locally distributed decision-making. Agent technology provides a natural way to address such problems supporting planners in simulating and evaluating different scenarios according to the modified manufacturing situation. Agents are intelligent software entities that expose flexible behaviors, cooperating, competing, and coordinating in order to achieve their goals. Such features are basic requirements for modeling scenarios in which single entities interoperate constituting (rising-up) a complex organization. Agents are commonly organized through multi-agent systems (MAS). MAS have been recognized as one of the technologies that would facilitate agile and intelligent manufacturing by providing manufacturing enterprises with the capabilities to meet the ever-increasing needs for flexibility, robustness and adaptability to the rapid changes occurring in the manufacturing environment [8]. Agent technology is well suited for the modeling of distributed and concurrent applications requiring a high degree of cooperation, and/or competition, with asynchronous communication; hence different communication and coordination protocols have been developed. The contract net protocol (CNP) was introduced by Smith and has represented the first work to use a negotiation process involving a mutual selection by both managers and contractors in distributed artificial intelligence. In this work a model to perform the announcing, bidding and awarding tasks, based on marginal costs has been used. The proposed SCOP system deals with supply-chain contexts featured by multi-site production, dynamic allocation, and multiple constraints, allowing decision makers to act on different parameters and negotiation rules, used by CNP, to derive different scenarios to be evaluated through a performance driven scenario-based analysis.

### 3 The detailed Supply Chain Operations Planning Problem

Besides traditional approaches to model the SCOP problem, in this work we added several detailed features to better model real industrial contexts. The main characteristics of the considered Detailed SCOP (DSCOP) problem, consisting in a dynamic multi-site production planning over a rolling horizon, are illustrated in this section. A SC system corresponding to a multi-site production structure is assumed as figure 1 shows.

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TIFF (LZW) decompressor  
are needed to see this picture.

Fig.1 - Supply chain structure from an industrial organization perspective  
(London et al. 2000, after Lambert et al. 1998).

In particular, the multi-site structure can be divided in different tiers characterizing the production of the items needed for manufacturing the finished products (end items) at the demanding organization level. Each tier is responsible for the production of a subset of items that, generally, are in turn composed by other component items. The independent (exogenous) customer demand of end items then generates a dependent (endogenous) demand for the component items needed at the various tiers of the SC (production suppliers side). Each tier comprises different organizations (production site), and each organization is composed by a set of work centers owning the resources used to manufacture some kinds of item. This structure leads to a dependent demand production optimization. Optimization with dependent demand has been widely faced in the literature. Linear and mixed integer programming (L&MIP) models have been proposed for MRP and MRP-II [11]; capacitated lot sizing models takes into account aggregate constraints on resource availability and the presence of setup costs [12] [13]. Recently, in [9] two linear programming models

have been compared to face the SCOP problem with planned lead times corresponding to fixed manufacturing and delivery times reasonably assumed for item production. Despite the great improvements in computation capability of commercial MIP solvers, most due to the development of effective mathematical techniques, the definition and solution of the complex decision problems in DSCOP is still tackling and often is perceived as an approach too distant from reality by managers. Nevertheless, in the rest of this section we present formally a mathematical model for the considered DSCOP problem, underlining the assumed simplified assumptions.

#### 3.1 Modeling assumptions

A planning period of length  $T$  is assumed and planning decisions must be taken in correspondence of time periods (also so-called *time buckets*)  $[t, t+1]$ ,  $t=0, 1, \dots, T$ . Note that the adopted time scale is arbitrary and may be adapted to different production scenarios (e.g., the unitary time bucket length may correspond to any fixed  $\Delta t$ ). Note also that usually the DSCOP should be dynamically solved on a rolling planning horizon  $H$ , i.e., revising the plan every  $H$  periods to take into account of changes, as for example new customer order arrivals. Let  $I$  the set of items that can be produced in the supply chain system, including both component and end items. The orders for end items received from the system customers are assumed known at the beginning of the planning period; note that the demand may correspond to actual orders or forecasts. A set of orders identifies for any end item  $i \in I$  and any time  $t \in [0, T]$  a demand  $D_{it}$  denoting the quantity of  $i$  requested at due date  $t$ . In general, the demand for an item  $i \in I$  can be assigned to a subset of sites composed in turn by one or more work centers owning the resources needed for the production of  $i$ . Then, the sets  $S_i$  and  $W_{si}$ , with  $s \in S_i$ , represent respectively the set of sites and work centers within a site compatible with the production of item  $i$ .

Each order demand  $D_{it}$  can be in general split in a set of  $n_i$  lots of size  $L_i$  such that  $L_i \geq L_{i,min}$ , being  $L_{i,min}$  a specified minimum lot size for  $i$ , and

$D_{it} = \sum_{h=1}^{n_i} L_i$ . Then the decision about the production

order  $i$  correspond to the decision about the associated lots. However, note that, for the sake of simplicity, in the formal problem definition we will continue to refer to the production of the whole item orders. A fundamental difference between the considered DSCOP and the SCOP described in the literature (e.g., in [9]) is the necessity of determining

the assignment of item orders first to the compatible production sites and then to the work centers within the sites. A planned lead time  $p_i$  is assumed for each item  $i \in I$ , corresponding to the estimation of the production time needed to complete the item, having assigned to the production of  $i$  the required resource capacity  $q_i$  (note that the planned lead times can be periodically revised according to the actually measured lead times). As planned lead times are in general longer than a single time period, the production of the items is executed on a sequence of consecutive buckets (*multi-period production*). A further relevant difference among the classic SCOP and the DSCOP here considered is that the assignment of orders to sites and work centers can be changed over the planning period: in particular, it has been assumed that the production of an order started in a work centre can be completed in a different work centre included in the same site with a negligible transfer cost, whereas a fixed transfer cost  $tc_{rs}$  is paid for each order moved from site  $r$  to site  $s$ . Taking into account the production structure of the considered items, a *Bill Of Material* (BOM)  $M=[m_{ij}: i,j \in I, i \neq j]$  matrix, whose elements denote the number of unit of item  $i$  needed for the production of item  $j$ , is specified. Then, given the set of end item orders characterized by their due dates, the endogenous gross demand for component items is generated by a backward BOM explosion. Note that raw material requirements are dealt with as demand for special items requested to external sites, i.e., not included in the controlled supply chain system. Each work centre  $j \in W$  includes a set of production resources in general corresponding to machines, tools, personnel and so on; an available maximum capacity  $c_{jt}$  is defined for work centre  $j$  which may depends on the time period  $t$  considered. In general the production of an order for an item may be on-time (i.e., completed at the required due date), early or tardy: in case of early production the order is not delivered before its due date and a unitary inventory cost  $\alpha_{it}$ , which may depends both on the item and the time period, is charged; on the other hand, tardy delivery are allowed incurring in a unitary backorder cost  $\beta_{it}$  for item  $i$  at period  $t$ .

### 3.2 DSCOP formal statement

The objective of the DSCOP problem is determining a plan for the multi-site production system corresponding to a MPS, that is, an assignment over time to the work centers of the item orders needed to satisfy the customer demand, taking into account the capacity of the available resources and minimizing a (weighted) sum of all the costs incurred. The formal

statement of the DSCOP problem then is the following. Given the demand for each item  $i$  and period  $t$  in the planning horizon that extends over  $T$  periods, we must determine the quantity of item  $i$  that is due at time  $t$ , the level of inventory for  $i$  available at the end of bucket  $t$ , and the quantity of item  $i$  backordered in bucket  $t$ ; in addition, for each work center we must determine the assigned production of items and capacity used for the production of such items in each bucket  $t$ . The DSCOP objective is the minimization of the sum of the incurred costs over the planning horizon, i.e., production, inventory, backordering costs plus fixed costs for the site and work centre assignment and possible production transfer costs. If, for the sake of simplicity, we disregard the possibility of transferring the production of lots of items between sites, the problem can be formulated as a MIP extending the LP formulation with balance equation in [9] as follows, introducing as decision variables:

- $Q_{it}$  the quantity of item order  $i$  completed at time bucket  $t$ ;
- $Y_{it}$  the level of inventory within period  $[t, t+1]$ ;
- $G_{it}$  the gross requirement of item  $i$ , i.e., the dependent demand for  $i$  induced by the production of other items including  $i$  as a component;
- $B_{it}$  the quantity of item  $i$  backordered at time  $t$ ;
- $Z_{it}$  the overall production capacity used for the production of item  $i$  in time bucket  $t$ ;
- $C_{jit}$  the production capacity of work centre  $j$  used for the production of item  $i$  in time bucket  $t$ ;
- $X_{its}$  the assignment of production of item  $i$  to site  $s$  in time bucket  $t$ ;
- $X'_{iww}$  the assignment of production of item  $i$  to work centre  $w$  in time bucket  $t$ .

$$\min \sum_{t=0}^T \sum_{i \in I} (\alpha_{it} Y_{it} + \pi_{it} Q_{it} + \beta_{it} B_{it} + \sum_{s \in S_i} f_{is} X_{sit} + \sum_{w \in W_{si}} f'_{iww} X'_{wit}) \quad (1)$$

subject to

$$Y_{it-1} + Q_{it} = D_{it} + G_{it} + Y_{it-1} - B_{it} + B_{it-1} \quad \forall i \in I, \forall t \quad (2)$$

$$G_{it-p_i} = \sum_{j \in I} Q_{jt} m_{ij} \quad \forall i \in I, \forall t \quad (3)$$

$$q_{it} Q_{it} = \sum_{t-p_i \leq s \leq t} Z_{is} \quad \forall i \in I, \forall t \quad (4)$$

$$Q_{it} \geq L_{t \min} \quad \forall i \in I, \forall t \quad (5)$$

$$Z_{it} = \sum_{j \in W_i} C_{jit} \quad \forall i \in I, \forall t \quad (6)$$

$$C_{jit} \leq c_{jt} X'_{jit} \quad \forall i \in I, \forall t, \forall j \in W_{si} \quad (7)$$

$$X'_{jit} \leq X_{sit} \quad \forall i \in I, \forall t, \forall s \in S_i, \forall j \in W_{si} \quad (8)$$

$$Y_{it}, Q_{it}, G_{it}, B_{it}, Z_{it} \geq 0 \quad \forall i \in I, \forall t \quad (9)$$

$$C_{jit} \geq 0 \quad \forall i \in I, \forall t, \forall j \in W_{si} \quad (10)$$

$$X_{sit}, X'_{jit} \in \{0,1\} \quad \forall i \in I, \forall t, \forall s \in S_i, \forall j \in W_{si} \quad (11)$$

In the objective (1)  $\pi_{it}$  represents the unitary production cost of item  $i$  in the time bucket  $t$ , whereas  $f_{is}$  and  $f'_{iw}$  are the assignment costs of item  $i$  respectively to site  $s$  and work centre  $w$ . Constraints (2) define the balance conditions for the production in each time buckets; constraints (3) impose the gross requirement in the time buckets identified by the planned lead times induced by the production of items; constraints (4) ensure the needed capacity is assigned for item production; constraints (5) impose the minimum lot size for item production; constraints (6) dispatch the capacity required for item production among the compatible work centres; constraints (7) and (8) define the site and work centre assignment to item production, and finally constraints (9), (10) and (11) impose the positivity and the binary nature of the variables.

The MIP formulation (1)-(11) should be considered a possible example of a mathematical programming model tackling some main features of the DSCOP. Such model must be further complicated if we need to introduce additional characteristics: as an example, modelling the transfer of item production from site (work centre) to site (work centre) over time requires the use of sequencing variables. Hence we can note in general that modelling and solving DSCOP by means of mathematical programming is based on the definition of rather complex models which usually lack in flexibility, i.e., which are not easy to extend or modify to account for the different real industrial organizations requirements in different industry contexts.

## 4 The Proposed Approach

In this paper, we want to design a framework to apply the agent theory to the particular logistic problem multi-site plant supply-chains. In a multi-site plant supply-chain, improving logistics represents one of the principal ways to reduce the end product costs and to improve the system's flexibility. If a mathematical solution was selected to manage this situation (see previous paragraph), a formalized and complex mathematical model is required reducing the flexibility and adaptability of the approach (especially to SME). Decentralized systems, like MAS, are characterized by higher flexibility. All this opens the way to the multi-agent approach the difficulty of which mostly lies in the need of an effective coordination system.

Furthermore, the drawback of a distributed system, consisting in the high amount of information that must be exchanged between sites has now less impact, thanks to technological advancement. So a multi-site plant could currently be managed by a set of heterogeneous intelligent agents with different features and goals, which interact to enhance both their performance and the system's. In this work we designed an approach allowing planning a multi-site manufacturing supply-chain by adopting a multi-agent architecture.

### 4.1 The Agent Architecture

A spurious control structure using a semi-hierarchical architecture with two different levels has been adopted [10]. This led to the simple but quite effective architecture showed in figure 2.

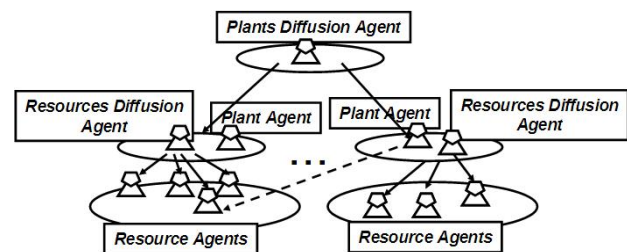


Fig.2 - The multi-agent system architecture.

Given a set of demands, the requests are sequentially processed, according to a priority list. The adopted priority rules are usually defined by the planner and are generally based on some common practice. In this way, the system favors demands processed first and gradually penalizes the following ones since the availability of the resources for processing these latter is progressively reduced by the assignments to previous ones. Mediator agents (plant and resources diffusion agents), perform the clustering operation starting from a demand order. They select the involved agents on the base of the order's features. The mediator agent also classifies the agents and divides them according to their output features and their capability of satisfying their tasks. Given the demand  $D_{it}$  for each item  $i$  period  $t$ , a Demand Agent (DA) deals with the Plant Diffusion Agents (PDA). According to plant capabilities, the PDA requests several Plants Agents (PA) to explore their own Resource Agents (RA) in order to build a bid for the item to be manufactured. Then the PDA evaluates the collected bids and selects the best proposal that communicates to the Demand Agent (DA). The PDA acts as a mediator and a switch within the control system, selecting messages to be exchanged among different kinds of agents and evaluating bids

according to some performance index (in our case the equation (1)).

#### 4.2 The System Decision Variables

Whenever multi-agent architectures including mediator agents are considered [14], their performances are usually influenced by the opportunities offered to the agents in generating different alternative bids. These opportunities, corresponding to decision variables, can be summarized in four different categories:

1. Supply-chain flexibility;
2. Lot size for item orders splitting;
3. Negotiation on production resources;
4. Task swapping (anticipation or delay of capacity allocation).

The first category can be evaluated by a *what-if analysis* varying the process and logistics flexibility associated with the modeled supply-chain. Lot sizing, which determines the number of lots composing an order item ( $D_{it}$ ), affects the planning flexibility in allocating working capacity. Negotiation on production resources explores different possibilities to find work centers with the required capacity. Finally, task swapping with respect to anticipation or delay limitations provides a further degree of improvement of a feasible capacity allocation. The rest of this section describes the way the opportunities (2, 3, 4), are used in the proposed system.

##### Supply-chain flexibility

The analysis of supply chain flexibility involves the consideration of the flexibility of the supply chain components and their relationships, in order to evaluate their impact on the whole system [15]. Supply chain flexibility takes into account two main aspects:

- (1) process flexibility of each supply chain plant, concerning the number of product types that can be manufactured in each production site (supplier or assembler); and
- (2) logistics flexibility, related to the different logistics strategies which can be adopted either to release a product to a market or to procure a component from a supplier.

The proposed SCOP system allows to evaluate both process flexibility (the manufacturing system flexibility), and logistics flexibility (the routing flexibility at the shop floor level), that is the ability of using alternative routes to move the work-in-process through different resources offering the

same processes. Through this type of analysis is then possible the production shifting of an item (component or final product) to different sites of a given stage of the supply chain, allowing reduction of the negative impact of demand and process variability on supply chain performance.

##### Lot sizing for item orders splitting

A demand  $D_{it}$  expresses the total quantity of item  $i$  requested at time  $t$ , which corresponds to a requested working capacity  $q_i$  on the compatible work centres in  $S_i$ . In general, the allocation of  $q_i$  could exceed the available capacity at given time  $t$  for a work center. Then a suitable strategy is to split  $q_i$  into a set of smaller dimension lots. In fact, the greater is the item quantity of a  $D_{it}$  the smaller are the chances to find a feasible allocation on a work center pool, satisfying the imposed constraints. On the other hand, too small lot sizes generate not acceptable set-ups and reordering costs. For this reason a trade-off has to be determined in order to balance planning flexibility provided by small lot dimension with costs due to splitting. The proposed approach allows splitting a demand  $D_{it}$  in a set of  $n_i$  lots of size  $L_i$ . The size of these lots can be determined through the scenario based-analysis capability of the proposed system. Such an analysis is performed starting from a minimum lot size for each item  $i$ , progressively increased of a fixed step in order to evaluate the consequent performance variation according to (1). The concept used by the proposed system can be described with an example showed in figure 4. Let us assume a constant demand for each bucket (the black thick line, Demand Flow, it is a theoretical representation of a one single piece flow production). Satisfying such demand would require a pure agile SC system, able to manufacture continuously variable lots in order to constantly chase the demand considering negligible set-up costs; in this case the SC system would be able to fulfill such demand producing at the same demand rate, with minimal (null) inventory and backlog costs. Nevertheless, in real life industrial contexts economic and production order lots have to be considered. Figure 4 shows (the step-wise blue line), the profile of the cumulative economic production lot for the constant demand flow, which would characterize the optimal production of a system with unlimited capacity. However, if the available capacity is limited, alternative routings and/or production anticipation/delay become necessary.

##### Negotiation on production resources

As stated above, the adopted multi agent system is based on mediator agent, which corresponds to the

PDA. The negotiation protocol is based on a CNP and it is represented in figure 3 of Appendix A. The negotiation protocol performs the announcing, bidding and awarding tasks, based on marginal costs. After the grouping operation made by the mediator agent each agent, belonging the first level, knows its goal and its suppliers. The agents, then, calculate their demands concerning input materials and send an announcement to their supplier cluster singled out by the mediator agent. If the agent that made the announcement is an independent agent, then it can satisfy the order and it can associate a maximum cost to its announcement: this cost is its marginal production cost. Otherwise, the agent will fix the maximum cost to infinite, so that some other agent will surely offer a better price. An agent bidder reads the announcement sent and calculates the marginal cost that it would sustain if it added the operations requested to its current set of operations. The agent sending the order reads the bids to select the most inexpensive one. Then it sends an award message to the bidding winner agent and a loser messages to the others. Since the proposed system is devoted to real industrial applications, a trade-off to balance the quality and speed of the system's responses has been investigated. For this reason, the negotiation process can be customized by the human planner creating a priority list of existing announcing, bidding and awarding rules and defining, for each rule, parameters and alternative agents' behaviours. A rule can include evaluation methods (i.e. balancing workload over resources) to guide mediator agent in awarding activity. So a heuristic procedure could be utilized to determine the marginal cost, in order to reduce computing time. The MAS planning engine elaborates the rules according to their priority order, and calculates, for each rule, an alternative planning-scenario providing the resulting performance index to the planner. Note that the proposed system includes a rule builder user interface through which is possible to define even complex multi-level conditional rules reflecting decisional processes typically performed from SC planners.

#### **Task swapping (anticipation or delay)**

After the awarding phase, a tasks swap phase has been added before the commitment and only after this phase the assignment of tasks to agents will be definitive. This has been done because an assignment process based on some priority rule, associated with a constrained production capability, does not guarantee a good solution for the system. In the swap phase, agents try to exchange some tasks that had been previously assigned to them, so

as to enhance the system performance, i.e. to reduce total costs expressed in (1), by acting on several relaxed constraints. Typical constraints on which it is possible to act on are alternative resources (resource space exploration), and capacity anticipation and delay on the same resource (time exploration). Resource space exploration refers to the possibility of using, for the task swapping, a resource different from the one a priori specified as preferred (after a checking of the production capability compliance), included in the same plant or in a different production site (in this last case a transport mission is evaluated according to a planned lead time and the cost computed). The resource space exploration allows the planning engine to resolve capacity unfeasibility at a given time. The alternatives relevant to time exploration correspond to the possibility of anticipating or delaying a task (swapping it with an other), on a resource within a range defined respectively by a maximum anticipation time and the corresponding inventory level and by a maximum admissible backordering time. The time exploration allows the planning engine to resolve capacity unfeasibility on a fixed resource. The planners, according to best practice common criteria, can combine exploration over space and time in order to launch a task swapping re-planning opportunity; he/she must also define the maximum admissible inventory level, and the maximum backordering time for each item  $i$ . After a verification of the capability constraints agents, involved in the swapping process, are forced to exchange tasks, which could be better performed by other agents. In the figure 4 the step-wise dark black line is a possible production profile generated by the agent negotiation and task swapping processes after a demand split value corresponding to the economic production lot: production anticipations are highlighted by dashed arrows, whereas delays by round-dotted arrows. Note that the maximum anticipation and maximum delay are constrained respectively by the maximum inventory level (gray line) and by the maximum backorder time (red line).

## **5 Discussion**

It is apparent that the approach to the DSCOP here presented corresponds to a heuristic method based on a decomposition of the decision process in a number of cooperating actors (the agents) playing different and complementary roles. We should note that exact optimization approaches to the DSCOP are also possible (e.g., based on mixed integer programming models). Nevertheless, the dimension

of the problem instances considered in real industrial context, that is, the number of items manufactured, of different sites belonging to a supply-chain and of the alternative routings to be explored is generally so high to make most of the time impractical the use of exact algorithms. In contexts with a flexible production mix, with flexible routings and assignments to be made in a multi-site supply chain, the use of a multi-agent architecture including supervisor and switch agents can successfully generate feasible plans incorporating decision maker's experience in the form of rules. This type of architecture provides solutions that can be explicitly understood and thus adopted by the planners since system agents "incorporating" the decision-maker's experience can drive negotiations towards an "expected-acceptable" solution hopefully near optimal. This is the type of approach generally preferred by small and medium size organizations. The research here presented focused on the integration of agent-based planning with existing systems used in manufacturing enterprises (in particular with ERP and MRP systems), and has been validated in industrial settings. The above claims are based on the following features emerged from the experience gathered during the implementation of the system in several industrial contexts:

- A agent architecture able to model medium multi-site and multi-distribution organizations;
- A meaningful representation of products structure through the use of family bills and bill of materials;
- Flexibility in managing shifts, working periods, overtime costs, exceptions, and bucket dependent resource capacity;
- Easy management of physical and logical constraints (productive and logistics);
- An extensive use of multiple in-memory simulation scenarios to facilitate the comparison of different strategies and the impact of manual modifications.

## 6 Conclusions

The proposed system is devoted to manage a SC, with respect to internal and external resources, over a multi-site manufacturing network. The designed allocation engine is based on a allocation procedure and it dispatches demand to production sites taking into account the limited resources capacity and trying to minimize the total aggregate cost even by using an improved heuristic task swapping procedure. The proposed system can support companies in dealing with DSCOP problems

through the evaluation of costs incurred in anticipating or delaying production activities, as well as in showing evidences of conflicts between commercial needs (demand fulfillment) and multi-site/multi-supplier constrained supply-chain network. The industrial adoption of this system appears to be still limited to the simplest functionalities. Anyway authors are improving the system by developing a new bidding process to fix drawbacks caused by fixing a sequential order for rule invocation, which strongly influence the order assignment to resources. A further comparison of performances provided by this system and traditional mathematical approaches is, currently, under investigation.



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### A Appendix

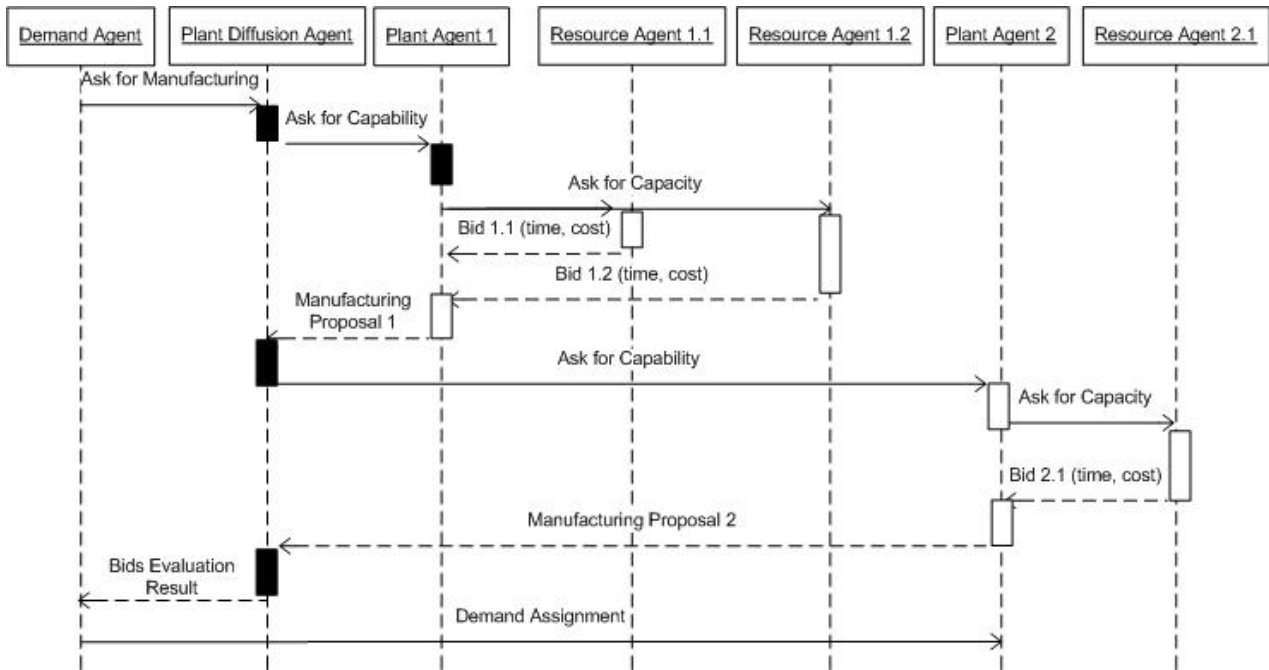


Fig.3 – Agent Negotiation Protocol.

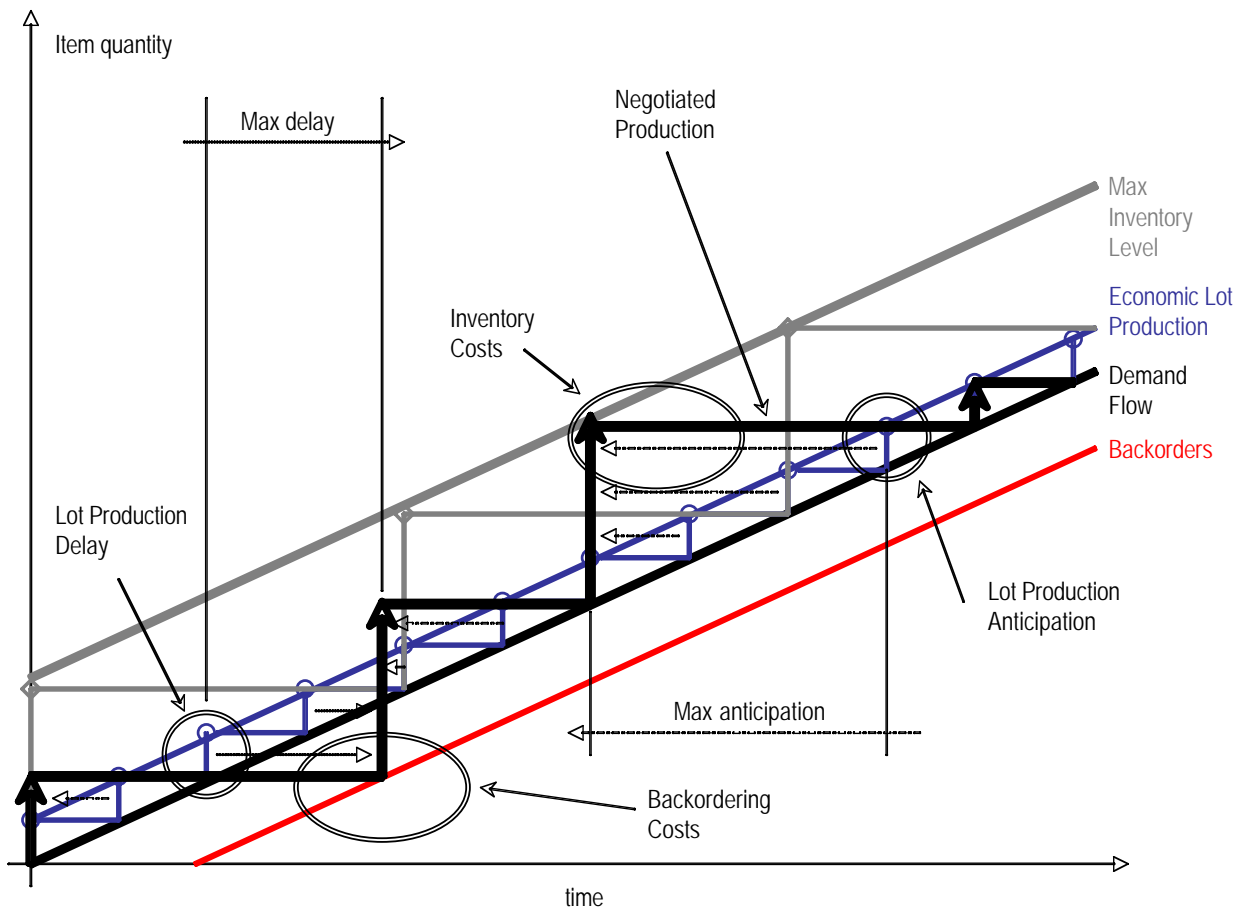


Fig.4 – An example of capacity allocation corresponding to a constant demand.