

# MULTI-AGENT NEGOTIATION IN A SUPPLY CHAIN

## *Case of the Wholesale Price Contract*

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**Abstract:** In this paper, we propose a multi-agent negotiation model for the wholesale price contract (price:  $W$ , quantity:  $Q$ ) in a supply chain with a retailer buying from several subcontractors. We assumed that the retailer stocks up from several subcontractors in order to face a market with fixed demand. Each subcontractor has a normal production capacity (CN) which can be increased until a maximal capacity (CM) but with an additional cost. The demand is superior to the sum of normal capacities and inferior to the sum of maximal capacities. Thereby, the negotiated and agreed price between the retailer and each subcontractor relies on the ordered quantity and the extra cost generated by any excess capacity (above the CN level). Under asymmetric informational context, we propose a multi-agent model which is a duplication of the considered supply chain; subcontractor agents negotiate a combination (price, quantity) in order to maximize their benefits and a retailer agent negotiates several combinations (price, quantity) with the different subcontractor agents in order to satisfy demand, allocate quantities and maximize its margin. Experimental results shows that the objective of reaching agreements and establish a long-lasting “win-win” partnership is totally reached but repartition of benefits is not so fair.

## 1 INTRODUCTION

In the current economic context, competition is no more between different “stand-alone” companies but between different groups of companies constituting different supply chains. Founding strong links of cooperation and synergy between companies of the same supply chain has become a key success factor. Therefore, companies try to establish a long-lasting partnership between them. Those relations are materialized by contractual engagements which are subject of negotiations where each contracting party tries to protect his interests in a long-lasting relationship. Several contract types have been investigated in the economic literature (Cachon, 2004) (Duvallat & al., 2006) (Gomez-Padilla, 2005). These researches have focused on the impact that these contracts may have on the performance of the supply chain and its actors. They converge to the point that such contractual modalities are fully integrated into the decision-making process of companies (Duvallat & al., 2006). Nevertheless, an

important aspect remains untreated (Cachon, 2004) which is the negotiation of those contractual relations. Those contracts were well studied in the economic literature but ignored as to the negotiation aspect. In order to investigate this important aspect, we propose in this paper a multi-agent negotiation system for a particular contract type which is the wholesale price contract. With this contract, the retailer pays the ordered quantity  $Q$  to a subcontractor at a unitary price  $W$ .

Automated negotiation has received a significant attention in the literature. Indeed, several approaches have been studied (Jennings & al., 2001); game-theoretic approaches, heuristic-based approaches, and argumentation-based approaches. The first kind of these approaches employs technics from game theory in order to establish the negotiation process and the strategies undertaken by the negotiator agents. These negotiation technics have the advantage and the ability of providing optimal solutions. However, they require long and important computation duration and capabilities. They also assume that negotiator agents have complete

information. The heuristic-based approach allows overcoming the limits of the game-theoretic approach, however, it doesn't produce optimal solutions but good solutions. This approach provides more flexibility for the designer of agents; models are based on more realistic assumptions, negotiator agents don't need to have complete information to evolve in the negotiation process and the computation requirements is pretty low. The argumentation-based approach is based on information exchange. Indeed, an argumentation-based model is a negotiation process whereby agents are allowed to send information in addition to their offers in order to influence the counterpart.

Among these approaches, we selected and used the heuristic-based approach for two main reasons; first, it allows dealing with more realistic assumptions and second, in our context, information exchange is asymmetrical at the beginning of the negotiation (for assumptions) and useless during the negotiation process.

In this paper, we propose a multi-agent negotiation model for the wholesale price contract (price:  $W$ , quantity:  $Q$ ) (Cachon, 2004) (Gomez-Padilla, 2005) (Spengler, 1950) in a supply chain with a retailer buying from several subcontractors. Each subcontractor has a normal production capacity (CN) which can be increased until a maximal capacity (CM) with an additional cost. For the goods produced above the CN level, each subcontractor has an additional cost which can be low or high according to his productive system. Therefore, the negotiated and agreed price with the retailer should rely on the ordered quantity and the additional cost caused by any excess capacity. On the other side, the retailer faces a market with fixed demand which is superior to the sum of normal production capacities and inferior to the sum of maximal production capacities of the different subcontractors. He must allocate quantities and agree on the wholesale prices with the subcontractors in order to maximize his benefits.

The information exchange is asymmetrical in the model. Public information are the fixed demand, the selling price and capacities (normal and maximal) of each subcontractor. Information concerning costs calculation systems of each actor are considered as private and not shared.

The proposed multi-agent model is a representation of the related supply chain; subcontractor agents negotiate a combination (price, quantity) in order to maximize their benefits and a retailer agent negotiates several combinations (price, quantity) with the different subcontractor agents in

order to satisfy demand, allocate quantities and maximize its margin.

The objective of the proposed model is to help agents reach an agreement for a long lasting partnership and establish a win-win relation which is a key success factor in every supply chain. The ideal objective is that repartition of benefits happen as fair as possible which means that repartition occur approximately according to the added-value of each actor (each actor costs relatively to the global chain costs).

The paper is organized as follows. The next section presents related works. In section 3, we present the mathematic modelling of the related supply chain. Section 4 describes the multiagent model including the architecture and the negotiation dynamic. Section 5 outlines experimental results. And finally, the last section contains concluding remarks and future works.

## 2 RELATED WORK

Coordination by contracts is one of the main problems in the supply chain management area. A contract is a convention between two or several parties ending to create between them a legal bond. This main problem has received significant attention. Indeed, several researches (Cachon, 2004) (Duvallat & al., 2006) (Gomez-Padilla, 2005) have investigated the impact that several contract types may have on the performance of a supply chain and its actors. Seven contract types have been studied, proposed and applied in order to find or to assure an efficient coordination where we maximize, at the same time, profit of the chain and profits of the different actors (Cachon, 2004) (Gomez-Padilla, 2005):

- The wholesale price contract which stipulates that the unit price is defined beforehand and does not change whatever is the ordered quantity for the contract duration.
- The quantity discount contract represents an improved variant of the wholesale price contract. The difference is that price is decreasing according to the bought quantity.
- The buy back contract stipulates that the supplier or subcontractor rebuys the unsold quantity from the retailer at a price agreed beforehand.
- The quantity flexibility contract represents a variant of the buy back contract. In this type, the supplier or the subcontractor rebuys the

minimum between the unsold quantity and a percentage agreed beforehand.

- The sales rebate contract stipulates that the supplier or subcontractor grants a rebate to the retailer for the bought units above a threshold prefixed in the contract.
- The revenue sharing contract stipulates that the retailer pays a fixed price (relatively low) to the supplier or the subcontractor and enlists to pour him a percentage of sold units.
- The reservation capacity contract stipulates that the retailer reserves a capacity at the supplier or the subcontractor. Consequently, he pays a price per reserved unit, a price per unit actually ordered from the reserved capacity and a price per ordered unit in excess.

Investigated researches converge to the point that those contractual modalities are fully integrated into the decision-making process of companies (Duvallat & al., 2006). Those researches (Duvallat & al., 2006) (Gomez-Padilla, 2005) (Cachon, 2004) essentially focused on how to identify the set of contracts that coordinate the supply chain and arbitrarily allocate its profit. The agreed contract is not a subject of negotiation process. In such cases, it seems that either the firm that offers the contract does not matter because the aim is the supply chain coordination. However, it is unlikely in practice that either firm makes a single offer which is considered as the final offer (Cachon, 2004). It is more convenient that companies exchange several offers and counter offers before they settle on some agreement. The negotiation aspect of those contracts remains untreated and additional research is surely needed on this issue (Cachon, 2004).

Among the approaches considering supply chains and especially negotiation in supply chains, the multi-agents systems is an approach spilt enough in the academic literature (Jiao & al., 2006). The choice of such paradigm is justified by the distributed nature of a supply chain. Indeed, every supply chain is composed generally by autonomous, reactive and proactive actors. Those features are the same of an agent (Ferber, 1995). Moreover, negotiation using multi-agent systems has received a significant attention in the literature and several approaches have been investigated (Jennings & al., 2001); game-theoretic approaches, heuristic-based approaches, and argumentation-based approaches. In the heuristic-based approach, which is the approach we picked out, several negotiation strategies have been proposed. Faratin implemented (Faratin, 2000) a multi-agent system in which agents make trade-

offs under informational uncertainty and resource limitations context. In order to make the trade-offs, agents employ an algorithm using the notion of fuzzy similarity. The authors' objective has been to find negotiation solutions that are beneficial for both parties. (Kraus, 2001) presented a strategic model of negotiation where a set of agents need to reach an agreement on a given issue. The model consists of a protocol for the agents' interactions, utility functions and strategies of the agents. The utility functions have been used to evaluate possible terminations of the negotiation and to respond consequently. (He & al., 2003) implemented a multi-agent system in which autonomous agents (seller agents and buyer agents) trade services. Those agents employ heuristic fuzzy rules and fuzzy reasoning mechanisms to determine the best bid to make given the state of the marketplace. (Zhang & al., 2005) presented a cooperative, multi-step negotiation mechanism for task allocation. This mechanism combines marginal utility gain and marginal utility cost to structure the search process. It searches over multiple attributes that reflects the concerns of both agents in the negotiation in order to find a solution that maximizes the agents' combined utility. In (Rahwan & al., 2007), the authors present a methodology for designing agent negotiation strategies. The authors' aim has been to provide some guidance for designers of strategies either in heuristic-based or argumentation-based approaches.

In this paper, we present a negotiation model which consists of the interaction protocol of agents and the decision-making model of each kind of agent. The agents use heuristics, trade-offs functions (reduce and Increase) and utility functions (margin) in order to reach agreements. The model differs from the proposed negotiation models not only by the implemented heuristics and trade-offs functions, but also because it is studied in a particular context which is assuring a long-lasting partnership by the wholesale price contract. The negotiation of the several contracts mentioned above has not been investigated. Those contracts were well studied in the economic literature but ignored as to the negotiation aspect.

### 3 MATHEMATIC MODELLING

The model is a supply chain composed by several subcontractors and a retailer (Figure 1). The retailer stocks up from several subcontractors in order to face a market with fixed demand  $D$ . Each subcontractor has a normal production capacity

( $CNi$ ) which can be increased until a maximal capacity ( $CMi$ ) with an additional cost.

$$\sum CNi < D < \sum CMi \quad (1)$$

In order to satisfy the demand, the retailer order from each subcontractor a quantity  $Qi$  ( $\sum Qi=D$ ) at a unitary price  $Wi$ .

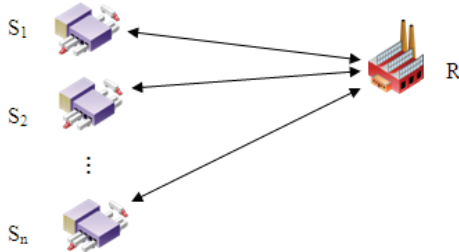


Figure 1: Considered supply chain.

### 3.1 Subcontractor<sub>i</sub>

Each subcontractor has a normal production capacity  $CNi$ . Until this capacity, he has a variable production cost  $VSi$ . He can raise it proportionally (overtimes, interim...) until a maximal capacity  $CMi$ , but with a higher variable cost  $V2Si$ . In addition to these variable costs, each subcontractor supports fixed costs  $FSi$ .

A subcontractor's costs  $CSi$  relies on the ordered quantity  $Qi$  and on the normal and maximal production capacities ( $CNi$ ,  $CMi$ ):

$$\begin{aligned} \text{If } Qi \leq CNi & \quad \text{Then } CSi = FSi + VSi * Qi \\ \text{If } CNi < Qi \leq CMi & \quad \text{Then } CSi = FSi + VSi * CNi + V2Si * (Qi - CNi) \end{aligned} \quad (2)$$

His profit margin  $MSi$  is as follows:

$$MSi = Wi * Qi - CSi \quad (3)$$

### 3.2 Retailer

The retailer faces a market with fixed demand  $D$ . His selling price  $P$  in the market is known. He stocks up from several subcontractors. He supports fixed costs  $FR$  (locals, staves ...) and variable costs per unit  $VR$  (finishing, wrapping...).

The retailer costs  $CR$  are: fixed costs  $FR$ , purchasing costs (financial transfers) from subcontractors and other variable costs of production and distribution per unit  $VR$ .

$$CR = FR + \sum Wi * Qi + VR * D \quad (4)$$

His profit margin  $MR$  is the difference between his sales on the final market and his whole costs:

$$MR = P * D - CR \quad (5)$$

### 3.3 The Supply Chain Margin and Costs

The global chain costs  $CCH$  is the sum of the different actors' costs:

$$CCH = CR + \sum CSi \quad (6)$$

The global chain margin  $MCH$  is the sum of the different actors' margin:

$$MCH = MR + \sum MSi \quad (7)$$

$CCH$  and  $MCH$  are not used in the negotiation model. They will be used in section 5 to evaluate if the found solutions present a fair margin repartition.

## 4 MULTI-AGENT MODEL

Modelling supply chains with the multi-agent paradigm has received in the last decade a significant attention (Jiao & al., 2006). This approach allows building autonomous entities (agents) which are able to communicate and interact in order to cooperate or reach an agreement.

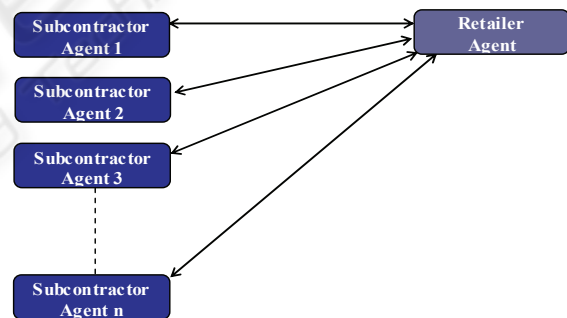


Figure 2: Multi-Agent Architecture.

### 4.1 Multi-Agent Architecture

The model, presented in Figure2, is a duplication of the considered supply chain. It is constituted of two kinds of agents: Subcontractor agent (SA) and Retailer agent (RA).

Several researches (Fiala, 2005) have demonstrated that sharing information is generally beneficial for both the supply chain and the actors that compose it. Indeed, knowing the whole information generally brings down problems to ordinary problems or linear programs. Nevertheless, in the real world, companies have always the reticence to share their information principally

fearing of being cheated or betrayed with contenders. So, we have chosen to analyze the considered model in an asymmetric informational context. Normal  $CN_i$  and maximal  $CM_i$  production capacities of each subcontractor are public. Information concerning costs calculation systems of each actor are considered as private and not shared.

This section presents objectives, acquaintances (the agents that it knows) and knowledge (static and dynamic) of each kind of agent.

#### 4.1.1 Subcontractor Agent

Each subcontractor Agent ( $SA_i$ ) has the objective of maximizing its profit margin  $MS_i$ .

Its only acquaintance consists of the RA. Its static knowledge represents information about its productive system: its normal production capacity  $CN_i$ , its maximal production capacity  $CM_i$ , its fixed costs  $FS_i$ , its variable cost for the normal capacity  $VS_i$  and its variable cost  $V2S_i$  for the production above the  $CN_i$  level. Its dynamic knowledge consists of the parameters of the negotiated contract: the price  $W_i$  and the quantity  $Q_i$ .

#### 4.1.2 Retailer Agent

The retailer Agent (RA) has two objectives: the first is to allocate quantities because the demand is superior to the sum of normal production capacities and inferior to the sum of maximal production capacities of the different subcontractors. The second is to maximize its profit margin  $MR$ .

The RA acquaintances consist of the set of all  $SA_i$ . Its static knowledge represents demand  $D$ , its selling price  $P$ , its fixed costs  $FR$ , its variable costs  $VR$ , normal and maximal production capacities of each subcontractor ( $CN_i$ ,  $CM_i$ ). Its dynamic knowledge consists of the states of the different  $SA_i$  during the negotiation (active, inactive, stand-by, busy) and the parameters of the negotiated contracts:  $(W_i, Q_i)$  with the different  $SA_i$ .

#### 4.2 Multi-Agent Dynamic

The negotiation is one-to-N multiple bilateral negotiation. The retailer agent negotiates with several subcontractor agents who have the same behaviours. The negotiating process, presented in Figure 3, is described with a UML sequence diagram. It describes exchanged messages (FIPA ACL Messages) between a retailer and a subcontractor agent.

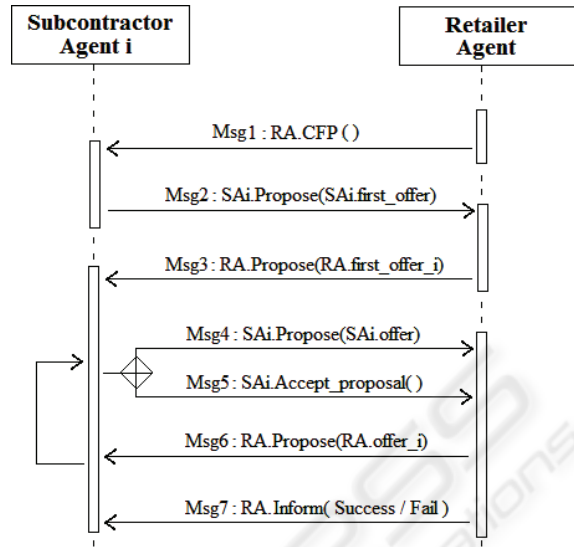


Figure 3: Negotiation process.

Before describing the dynamic, we define here the variables used in the next procedures:

$k$  : the  $k^{th}$  iteration of the negotiation process

$SA_i$  : Subcontractor Agent number  $i$

$SA_i.Q(k)$  : the quantity proposed in the  $k^{th}$  iteration

$SA_i.W(k)$  : the price proposed in the  $k^{th}$  iteration

$SA_i.offer(k)$  : the amount charged ( $W*Q$ ) in the  $k^{th}$  iteration

$SA_i.Min\_turnover$  : the min accepted amount in the negotiation =  $CS_i$

$SA_i.Begin\_turnover$  : the amount proposed by  $SA_i$  at the start of negotiation

$SA_i.Hoped\_turnover$  : the hoped amount

$SA_i.state$  : state of the  $SA_i$  in the negotiation process. Possible values are {active, inactive, stand-by, busy}. This variable is used by RA to qualify the evolution of each  $SA_i$  in the negotiation

RA : Retailer Agent

$RA.Q_i(k)$  : the quantity proposed to  $SA_i$  in the  $k^{th}$  iteration

$RA.W_i(k)$  : the price proposed to  $SA_i$  in the  $k^{th}$  iteration

$RA.offer_i(k)$  : the charged amount ( $W_i*Q_i$ ) to  $SA_i$  in the  $k^{th}$  iteration

$RA.offer(k)$  : the sum of charged amounts ( $\sum W_i*Q_i$ ) in the  $k^{th}$  iteration

$RA.Min\_turnover$  : the min accepted (global) amount =  $CR$

$RA.Begin\_turnover$  : the global amount (including offers to all the  $SA_i$ ) proposed by RA at the start of negotiation

$RA.Hoped\_turnover$  : the hoped (global) amount

The  $Begin\_turnover$  and  $Hoped\_turnover$  influence significantly the negotiation. But those parameters can be initiated differently according to the business or to the commercial. In our model, we

assumed that  $\text{Begin\_turnover} = 1.5 * \text{Min\_turnover}$  and  $\text{Hoped\_turnover} = 1.2 * \text{Min\_turnover}$ . But the model is generic and other values can be tested. We can even assume different values for each agent.

In addition to these variables, we use the following function to send messages from a source agent to a destination agent:

Send (Msg, Source, Destination)

The negotiation process is initiated by the RA. It sends a “call for proposition” (Msg1:RA.CFP) to the different SAi. Therefore, each SAi generates its first offer (Msg2) with quantity equal to its maximal capacity and price satisfying the SAi.Begin\_turnover.

Msg2: SAi.Propose (SAi.first\_offer)

1. SAi.Q(0) = Cmi
2. SAi.W(0) = SAi.Begin\_turnover / SAi.Q(0)
3. SAi.offer(0) = SAi.W(0) \* SAi.Q(0)
4. Send ( (SAi.W(0),SAi.Q(0)) , SAi , RA )

The RA collects the first offers of the different SAi. It generates its first offers (Msg3) to the different SAi. It allocates quantities in function of received prices (Msg3: line 1); from the cheapest to the most expensive. According to the allocated quantities and to its RA.Begin\_turnover, the RA tries, while calculating prices, to minimize the difference with those received from SAi (Msg3: line 3 to 5). Therefore, it sends offers to the SAi (Msg3: line7).

Msg3: RA.Propose (RA.first\_offer)

1. Allocate quantities on SAi
2. RA.offer(0) = RA.Begin\_turnover
3. Part = (  $\sum \text{SAi.Offer}(0) - \text{RA.Offer}(0)$  ) / D
4. **For Each** SAi
5. RA.Wi(0) = SAi.W(0) – Part
6. RA.offer\_i(0) = RA.Wi(0) \* RA.Qi(0)
7. Send ( (RA.Wi(0),RA.Qi(0)) , RA , SAi )
8. **End For**

A reiterated process of offer/counter-offer is set up (Msg4, Msg5, Msg6).

If the SAi receives an offer satisfying its SAi.Hoped\_turnover, it sends its acceptance to the RA. Also, if it receives an offer satisfying the SAi.Min\_turnover and equal to the last received offer it sends its acceptance (Msg4: line 1, 2).

On the other hand, for each new offer, the SAi adopts the charged quantity by the RA (Msg4: line 4), applies a reduction to its last offer while SAi.Min\_turnover is respected (Msg4: line 5 to 10), determines accordingly the price (Msg4: line11) and sends its proposition to the RA (Msg4 : line 12). The

reduction is calculated according to the following function:

$$\text{reduce}(X, Y) = \frac{(X - Y)}{2} * \varepsilon \quad (8)$$

Where:

X = The last made offer by the SAi : SAi.Offer(k)  
 Y = The last made offer by the RA to SAi : RA.offer\_i(k)  
 $\varepsilon$  = parameter determined experimentally = 0.2

This function allows differentiating the made reductions from iteration to another. Indeed, more the negotiation advances more the reduction decrease. This function contains a parameter  $\varepsilon$  which has to be determined experimentally. This parameter is crucial for the efficiency of the negotiation because it determines the steps made in each iteration; we have to avoid an efficient negotiation process but very long-lasting and a rapid process but inefficient. Several values have been experimented for the parameter  $\varepsilon = \{0.1, 0.2, 0.3 \text{ and } 0.4\}$ . The most convenient value is 0.2.

Msg4: SAi.Propose (SAi.offer)

1. **If** ( RA.offer\_i(k)  $\geq$  SAi.Hoped\_turnover ) OR ( ( RA.offer\_i(k) = RA.offer\_i(k-1) ) AND ( RA.offer\_i(k)  $\geq$  SAi.Min\_turnover ) ) **Then**  
 Send ( Acceptance , SAi , RA )
2. **Else**
3. SAi.Q(k) = RA.Qi(k)
4. R = reduce( SAi.Offer(k-1) , RA.offer\_i(k) )
5. **If** (SAi.Offer(k) – R) > SAi.Min\_turnover **Then**  
 SAi.Offer(k) = SAi.Offer(k-1) – R
6. **Else**  
 SAi.Offer(k) = SAi.Offer(k-1)
7. **End If**
8. SAi.W(k) = SAi.Offer(k) / SAi.Q(k)
9. Send ( (SAi.W(k),SAi.Q(k)) , SAi , RA )
10. **End if**

The RA collects the offers of all SAi. It updates the state of each SAi; if one of them made a satisfying offer, then, this one is set on stand-by (Msg6 : line 2 to 4). If it made an offer equal to its last offer which means that it can't evolve anymore in the negotiation, then, it is considered as inactive (Msg6 : line 5 to 7). After that, the RA checks the efficiency of the quantities' allocation(Msg6 : line 9). Then, it generates its offers to the SAi not set on stand-by; it applies an increase to the last made offers while RA.Min\_turnover is respected (Msg6 : line 10 to 15). The increase is calculated according to the same principle of the subcontractor's reduction function but with different parameters:

$$Increase(X, Y) = \frac{(X - Y)}{2} * \varepsilon \quad (9)$$

Where:

X = The last made offer by all the SA:  $\sum SA_i.offer(k)$

Y = The last made offer by the RA to all the SA :  $RA.offer(k)$

$\varepsilon$  = parameter determined experimentally = 0.2

Prices are calculated according to the made increase and to the assigned quantities to each SAi (Msg6: line 16 to 18). The RA sends then its proposition to each active SAi (Msg6 : line 20).

Msg6: RA.Propose (RA.offer)

//UPDATE STATES

```

1. For Each SAi
2.   If SAi.Offer(k) ≤ (RA.Hoped_turnover/SAi.Q(k))
      Then
3.     SAi.state = stand-by
4.   End If
5.   If ( SAi.Offer(k) = SAi.Offer (k-1) ) Then
6.     SAi.state = inactive
7.   End If
8. End For
9. Check_quantities_efficiency ( )
    
```

//UPDATE OFFERS

```

10. I = Increase (  $\sum SA_i.offer(k)$  , RA.offer(k-1) )
11. If RA.Offer(k-1) + I ≤ RA.Min_turnover Then
12.   RA.Offer(k) = RA.Offer(k-1) + I
13. Else
14.   RA.Offer(k) = RA.Offer(k-1)
15. End If
16. Part = (  $\sum SA_i.offer(k)$  – RA.offer(k) ) / D
17. For Each SAi Having ( SAi.state = active )
18.   RA.Wi(k) = SAi.W(k) – Part
19.   RA.offer_i(k) = RA.Wi(k) * RA.Qi(k)
20.   Send ( (RA.Wi(k),RA.Qi(k)) , RA , SAi )
21. End For
    
```

With the heuristic Check\_quantities\_efficiency(), the RA verifies if the quantities' allocation made in the last iteration is efficient. Indeed, reducing the ordered quantity to a subcontractor agent can have as effect a big rise of the charged price from the latter (line3:  $SA_i.W(k) > \beta * SA_i.W(k-1)$ ). A big rise of price can be regarded differently according to the business or to the commercial.  $\beta$  is a generic parameter which can be generated appropriately according to the context. In our experiments,  $\beta=1.4$ . If reducing the ordered quantity to a SA has produced a big rise of the charged price from the latter, the RA reviews its quantities' allocation; it cancels the made reduction of quantity to this subcontractor agent and makes it to other active or in stand-by subcontractor agent in function of prices from the most expensive to the cheapest (line 8 to 26).

Check\_quantities\_efficiency ( )

Qa : the quantity to reapportion

```

1. Qa = 0
2. For Each SAi Having ( SAi.state = active )
3.   If ( SAi.W(k) >  $\beta * SA_i.W(k-1)$  ) Then
4.     RA.Qi(k) = RA.Qi(k-1)
5.     Qa = Qa + (RA.Qi(k-1) – RA.Qi(k))
6.     SAi.state = busy
// reducing Qa from other active or in stand-by SA in
function of prices from the most expensive to the cheapest
7.   While (Qa > 0)
8.     max_w = 0 , indmax = -1
9.     For Each SAj Having ( SAj.state = active )
10.      If (max_w < SAj.w(k)) Then
11.        max_w = SAj.w(k)
12.        indmax = j
13.      End if
14.    End For
15.    If (indmax = -1) Then
16.      For Each SAj Having (SAj.state=stand-by)
17.        If (max_w < SAj.w(k)) Then
18.          max_w = SAj.w(k)
19.          indmax = j
20.        End if
21.      End For
22.      SAj.state = active
23.    End If
24.    If (indmax <> -1) Then
25.      RA.Qj(k) = RA.Qj(k) – Qa
26.    End If
27.  End While
28. End If
29. End For
30. For Each SAi Having ( SAi.state = busy )
31.   SAi.state = active
32. End For
    
```

The reiterated process of offer/counter-offer is engaged till the RA terminates the negotiation either by sending “success” or “fail” to each SAi involved in the negotiation (Msg7:RA.Inform(Success/Fail)). When the state of each SAi is either stand-by or inactive and an agreement is reached with at least some SAi able to respond to the demand D, the RA stops the negotiation and informs the counterparts of “success” of the negotiation. When a number of maximal iterations is reached without attaining an agreement, the RA stops the negotiation and informs the counterparts of the “fail”.

## 5 EXPERIMENTS

We have implemented this model with JADE platform (Bellifemine & al., 2007) which is one of the most known MAS platforms.

Table 1: Experimental Results

Assumptions		Margin	Contracts	
Case1	R	P=80 D=500 FR=10000 VR=15	10924.969	C1 to C2
	S1	CN=350 CM=420 FS=4000 VS=10 V2S=13	541.249	C1 (22.974, 350)
	S2	CN=100 CM=150 FS=1500 VS=12 V2S=14	133.780	C2 (23.558, 150)
Case2	R	P=5 D=1000 FR=1000 VR=1	528.907	C1 to C2
	S1	CN=500 CM=550 FS=1000 VS=0.5 V2S=0.9	38.357	C1 (2.424, 550)
	S2	CN=400 CM=500 FS=800 VS=0.7 V2S=1	7.735	C2 (2.528, 450)
Case3	R	P=3 D=10000 FR=5000 VR=0.3	4469.648	C1 to C3
	S1	CN=2000 CM=2400 FS=2000 VS=1 V2S=1.2	70.359	C1 (2.035, 2000)
	S2	CN=4000 CM=4300 FS=4000 VS=0.6 V2S=1.1	549.893	C2 (1.692, 4300)
S3	CN=3500 CM=3700 FS=3500 VS=0.7 V2S=1.1	10.099	C3 (1.67, 3700)	
Case4	R	P=40 D=500 FR=3000 VR=8	3551.001	C1 to C3
	S1	CN=150 CM=190 FS=1600 VS=6 V2S=7.5	329.275	C1 (18.861, 150)
	S2	CN=220 CM=250 FS=2000 VS=5 V2S=7	1369.716	C2 (18.718, 250)
S3	CN=80 CM=100 FS=1200 VS=7 V2S=7.8	24.006	C3 (19.4, 100)	
Case5	R	P=15 D=3000 FR=4000 VR=3	4193.881	C1 to C4
	S1	CN=800 CM=850 FS=4000 VS=4 V2S=5.5	175.882	C1 (9.001, 850)
	S2	CN=850 CM=870 FS=5000 VS=3.5 V2S=5	347.626	C2 (10.444, 770)
	S3	CN=700 CM=800 FS=3000 VS=4.5 V2S=6.2	32.889	C3 (8.503, 800)
S4	CN=500 CM=580 FS=2000 VS=5.2 V2S=7	149.719	C4 (9.154, 580)	
Case6	R	P=24 D=860 FR=750 VR=5	3805.19	C1 to C4
	S1	CN=230 CM=260 FS=850 VS=8 V2S=9.2	578.726	C1 (13.633, 260)
	S2	CN=340 CM=350 FS=110 VS=7 V2S=8	1267.429	C2 (13.792, 350)
	S3	CN=160 CM=200 FS=700 VS=8.5 V2S=9.5	37.807	C3 (13.111, 160)
S4	CN=70 CM=90 FS=450 VS=9 V2S=10.5	24.845	C4 (14.609, 90)	
Case7	R	P=20 D=1200 FR=2400 VR=4	2292.64	C1 to C4
	S1	CN=380 CM=410 FS=700 VS=9 V2S=10.5	136.443	C1 (11.149, 410)
	S2	CN=300 CM=350 FS=600 VS=9.5 V2S=11	53.5393	C2 (11.581, 350)
	S3	CN=250 CM=350 FS=500 VS=10 V2S=11	272.231	C3 (13.217, 240)
S4	CN=150 CM=200 FS=350 VS=11 V2S=12	110.290	C4 (13.551, 200)	
Case8	R	P=30 D=1000 FR=800 VR=6	5509.687	C1 to C5
	S1	CN=200 CM=230 FS=1000 VS=10 V2S=12	666.035	C1 (17.504, 230)
	S2	CN=370 CM=380 FS=1500 VS=9 V2S=10.5	1780.564	C2 (17.672, 380)
	S3	CN=150 CM=200 FS=900 VS=11 V2S=12	169.872	C3 (18.132, 150)
	S4	CN=100 CM=150 FS=500 VS=11.5 V2S=13	359.962	C4 (17.733, 150)
S5	CN=80 CM=90 FS=300 VS=12.5 V2S=14	128.878	C5 (17.431, 90)	
Case9	R	P=15 D=1080 FR=500 VR=3	3585.035	C1 to C5
	S1	CN=250 CM=280 FS=700 VS=5 V2S=6.5	2.899	C1 (7.671, 280)
	S2	CN=200 CM=220 FS=600 VS=5.3 V2S=6	39.157	C2 (9.059, 170)
	S3	CN=300 CM=310 FS=900 VS=4.5 V2S=5	104.657	C3 (7.756, 310)
	S4	CN=110 CM=145 FS=500 VS=5.8 V2S=6.5	51.727	C4 (9.773, 145)
S5	CN=120 CM=145 FS=470 VS=6 V2S=6.6	10.022	C5 (9.413, 145)	
Case10	R	P=22 D=5000 FR=12000 VR=7	5407.145	C1 to C5
	S1	CN=1200 CM=1250 FS=8000 VS=4 V2S=6	438.674	C1 (10.83, 1250)
	S2	CN=900 CM=1000 FS=6000 VS=5 V2S=6.5	476.361	C2 (13.635, 750)
	S3	CN=1000 CM=1150 FS=7000 VS=4.5 V2S=6.2	592.58	C3 (11.323, 1150)
	S4	CN=600 CM=680 FS=3500 VS=5.5 V2S=7	355.438	C4 (11.346, 680)
S5	CN=1100 CM=1170 FS=7500 VS=4.2 V2S=6	549.799	C5 (11.187, 1170)	

The implemented model differs from the iterated contract net protocol (FIPA, 2002) because a Call for propositions is sent only at the beginning and there is no limitation of time to respond in each iteration but there is a limitation in the number of maximal iterations. Moreover, the RA can qualify its contenders with states and acts with each SAi in the negotiation according to its state which is not the

case in the iterated contract net protocol. For example, the RA can put a SAi into a standby state in some iterations and then reinstate it in the negotiation process.

The experiments done allowed us to verify if the proposed model can lead agents to reach an agreement. Table1 presents some examples of our experiments. These examples approach real



industrial cases. We assumed that different subcontractors' profiles exist: those who have invested to automate their work process and consequently have high fixed costs and relatively low variable costs, and those who didn't invest and consequently have low fixed costs and relatively high variable costs. In the case 1, we took as assumptions a retailer negotiating with 2 subcontractors. The retailer respond to a fixed demand  $D=500$ , his selling price  $P$  is 80, he supports fixed costs  $FR=10000$  and variable costs per unit  $VR=15$ . The first subcontractor  $S1$  has a normal capacity  $CN=350$ , a maximal capacity  $CM=420$ , fixed costs  $FS=4000$ , variable cost for the normal capacity  $VS=10$  and variable cost  $V2S=13$  for the production in excess (above the  $CN$  level). The second subcontractor  $S2$  has a normal capacity  $CN=100$ , a maximal capacity  $CM=50$ , fixed costs  $FS=1500$ , variable cost for the normal capacity  $VS=12$  and variable cost  $V2S=14$  for the production in excess. After simulation, the agreed contracts were:  $C1(22.974, 350)$  and  $C2(23.558, 150)$ .

The implementation of this model has been made in two phases. First, we noticed that agreements can be reached but sometimes with illogical prices. In the case 1, agreed contracts were:  $C1(22.926, 420)$  and  $C2(37.487, 80)$ . As noticed, it's illogic to negotiate, for the same product, price around 22 with the first SA and around 37 with the second SA. Such illogical prices are generated when the quantity charged by the RA to a SA is relatively low. Thus, we added the heuristic `Check_quantity_efficiency()` in the decision-making process of the RA. This heuristic allows the RA to verify if the quantities' allocation made in the last iteration is efficient and to review it if necessary. Experiments have demonstrated that there are no more illogical negotiated prices. With the heuristic `Check_quantity_efficiency()`, agreed contracts in the case 1 were :  $C1(22.974, 350)$  and  $C2(23.558, 150)$ .

Among the experiments done, we found some cases where results are the same with the two models. In such cases, the quantities' allocation had no big impact on prices (Table1: Cases2, 3, 5, 10). But, for many other examples, as those presented in Figure4, the quantities' allocation has produced a big rise in at least one of the negotiated prices.

Figure 4 presents the min and the max prices agreed for each model. We notice that without the heuristic `Check_quantity_efficiency()`, the difference between the min and the max agreed prices is huge which is illogic. Nevertheless, using `Check_quantity_efficiency()` allows the RA to negotiate quite prices which is more realistic.

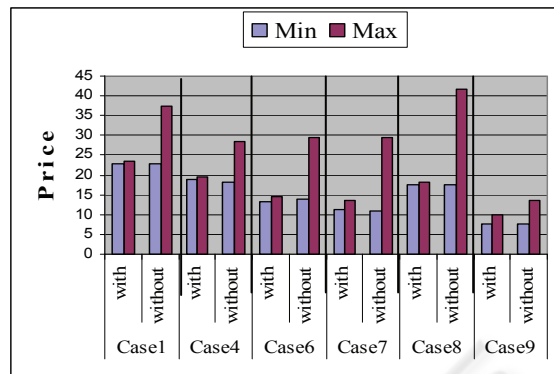


Figure 4: Comparison with/without `Check_quantity_efficiency()`.

The objective of the proposed model is to help agents reach agreements for a long lasting partnership and establish a win-win relation which is a key success factor in every supply chain. This objective has been largely reached. But, the ideal objective is that repartition of benefits happen as fair as possible which means that margin's repartition has to occur according to the costs of each actor relatively to the chain costs. Figure 5 presents a fair repartition and the results we found (Model repartition). We conclude that agents certainly reach an agreement to establish a win-win long lasting partnership but the repartition is not so fair. Agents have to be more cooperative to reach more equitable repartition of benefits.

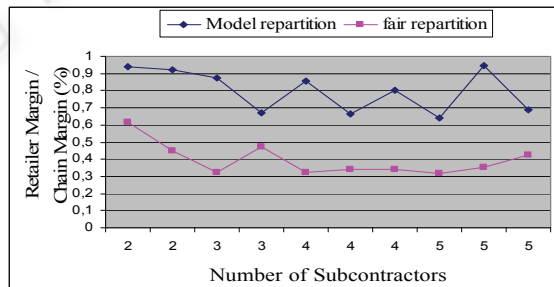


Figure 5: Comparison fair repartition (CR/CCH) –Model repartition (MR/MCH).

## 6 CONCLUSIONS AND FUTURE WORKS

In this work, we focused on a supply chain constituted by several subcontractors and a retailer in a particular contractual context which is the wholesale price contract (Price:  $W$ , Quantity:  $Q$ ). We assumed that the retailer stocks up from several

subcontractors in order to face a market with fixed demand. Each subcontractor has a normal production capacity (CN) which can be increased until a maximal capacity (CM) but with an additional cost. However, the demand is superior to the sum of normal capacities and inferior to the sum of maximal capacities. Thereby, the negotiated and agreed price between the retailer and each subcontractor relies on the ordered quantity and the extra cost generated by any excess capacity (above the CN level). The objective of the proposed model is to help actors in an asymmetric informational context to reach agreements for a long lasting partnership via the wholesale price contract and establish a win-win relation which is a key success factor in every supply chain. The ideal objective is that repartition of benefits happen as fair as possible which means that it occurs approximately according to the added-value of each actor (each actor costs relatively to the global chain costs).

To handle this problem, we have chosen the multi-agent approach. The model is a representation of the related supply chain; subcontractor agents negotiate a combination (price, quantity) in order to maximize their benefits and a retailer agent negotiates several combinations (price, quantity) with the different subcontractor agents in order to satisfy demand, allocate quantities and maximize its margin. The model has been implemented in two phases. First, we have found that agreements are reached but sometimes with illogical prices. Then, we added the `check_quantity_efficiency()` in the decision-making process of the RA. This heuristic allows the RA to verify if the quantities' allocation is efficient and to review it if necessary. Since, we found agreements with logical prices.

Experiments have demonstrated that agreements are possible. The objective of assuring a long-lasting partnership via the wholesale price contract is largely reached and a win-win relation can be established. However, the ideal objective of making the repartition as fair as possible is not totally reached and more investigation has to be done.

This research has several perspectives. First, we intend to extend the proposed model by making agents more cooperative in order to reach a more fair repartition of benefits under incomplete informational context. This can be done by integrating learning technics in agents or by treating the problem as a multicriteria problem. Second, we plan to treat the model with a stochastic demand. And finally, we intend to propose a negotiation model combining several contract types.

## REFERENCES

- Bellifemine, F., Caire, G. and Greenwood, D., 2007. *"Developing Multi-Agent Systems with JADE"*. John Wiley & Sons, Chichester, UK.
- Cachon, G.P., 2004. *"Supply Chain Coordination with Contracts"*, In S. Graves & T. de Kok (Eds.), *Handbooks in Operations Research and Management Science*. North Holland Press.
- Duvallet, J., Gomez-Padilla, A., LLERENA, D., 2006. *"Approche économique de la coordination dans les chaînes logistiques"*. MOSIM'06. Rabat, Maroc.
- Faratin, P., 2000. *"Automated service negotiation between autonomous computational agents"*. Ph.D. thesis, University of London, Queen Mary and Westfield College, Department of Electronic Engineering.
- Ferber, J., 1995. *"Les Systèmes Multi-Agents, vers une intelligence collective"*. InterEdition. Paris.
- Fiala, P., 2005. *"Information sharing in supply chains"*. Omega, Volume 33, Issue 5, Pages 419-423.
- FIPA, 2002. *"FIPA Iterated Contract Net Interaction Protocol Specification"*, Foundation for Intelligent physical agents, <http://www.fipa.org/specs/fipa00030/>
- Gomez-Padilla, A., 2005. *"Modélisation des relations verticales : une approche économique et logistique"*. PhD Thesis. I.N.P. de Grenoble. September 2005.
- He, M., Leung, H., Jennings, N. R., 2003. *"A fuzzy logic based bidding strategy for autonomous agents in continuous double auctions"*. IEEE Transaction on Knowledge and Data Engineering 15(6):1345-1363.
- Jennings, N., Faratin, P., Lomuscio, A., Parsons, S., Sierra, C., Wooldridge, M., 2001. *"Automated negotiation: Prospects, methods and challenges"*. International Journal of Group Decision and Negotiation 10, 199-215.
- Jiao, J., You, X., Kumar, A., 2006. *"An agent-based framework for collaborative negotiation in the global manufacturing Supply Chain network"*, Robotics and Computer-Integrated Manufacturing, Volume 22, Issue 3, Pages 239-255.
- Kraus, S. 2001. *"Strategic Negotiation in Multi-Agent Environments"*. Cambridge, MA: MIT Press.
- Rahwan, I., Sonenburg, L., Jennings, N. R. and McBurney, P., 2007. *"Stratum: A methodology for designing heuristic agent negotiation strategies"*. International Journal of Applied Artificial Intelligence, 21 (6). pp. 489-527.
- Spengler, J., 1950. *"Vertical integration and antitrust policy"*. Journal of Political Economy. 347-52.
- Zhang, X., Lesser, V., and Podorozhny, R., 2005. *"Multidimensional, multistep negotiation for task allocation in a cooperative system"*. Autonomous Agents and Multi-Agent Systems, Vol. 10, No. 1, pp. 5-40.