# USING MULTI-AGENT SYSTEM
# FOR DYNAMIC JOB SHOP SCHEDULING[1]

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Keywords:     Multi-agent system, Dynamic scheduling, Job shop, Simulated annealing, Reactive agent

Abstract:     Today's industries need more flexible scheduling systems able to produce new valid schedule in response to the modifications concerning orders, production processes and deliveries of materials. This paper introduces a multi-agent system applied to a job shop dynamic scheduling problem in which new production orders or deliveries arrive continuously and affect the already scheduled plan. We have solved the problem by: i) coupling reactive and pro-active agent behavior; and ii) implementing a stochastic method - simulated annealing - into agent's behavior. The job shop scheduling system is implemented using various types of agents whose interactions make the global state of the system move from a solution to another by continuously adapting to the changes from the environment. In this perspective, the interactions between the agents representing the client job orders, the production centers and the material stocks result in the assignment of operations and the plan for stock movements. Our experimental results show that, by modifying the classical agent-based message scheme, the integration of stochastic approach and multi-agent based technology could improve dynamic scheduling problems for a small to medium size problem space.

## 1   INTRODUCTION

Most current planning and scheduling systems in manufacturing industries rely on stationary properties of the production process but this assumption has been unrealistic, given the possibilities of machine faults, multiple delays and urgent incoming orders. After receiving the modifications concerning orders, production processes, material deliveries, the provisional plan rapidly becomes invalid. The responsible persons of production lines want to know the impacts of these changes on scheduling in order to take an immediate decision. In that context, today's industries need more flexible scheduling systems which react dynamically.

This paper introduces a multi-agent system applied to a job shop scheduling problem in a dynamic environment in which the above-mentioned changes arrive continuously and affect the existing production schedule. The problem has been solved by:

a) Coupling reactive and pro-active agent behaviors to solve the dynamic issues;

b) Emerging the schedule through the agent interactions;

c) applying a stochastic method - *simulated annealing* - as an optimization technique.


This work has been carried out in collaboration with an industrial partner (TI-Informatique in Valais, Switzerland) which wanted to replace the scheduling module integrated in their software product (Visual Prod), and an academic institute (ICARE-IsNet) for integrating the two systems – VisualProd and the multi-agent system.

This paper is organized as follows: In section 2, we outline a general definition of job shop scheduling and some problems which must be taken into consideration in a *dynamic* environment. And then we introduce our approach. Section 3 is devoted to detail the formulation of the optimization function and the technique of simulated annealing. The description of each agent is given in section 4. Section 5 presents a simple example to show how our agents work to produce a production schedule. In section 6, we discuss our experimental results and general conclusions are given in section 7.

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## 2  PROBLEMS OF JOB SHOP SCHEDULING IN DYNAMIC ENVIRONMENT

### 2.1  General definition

A job shop is a manufacturing environment where a set of m jobs (or tasks) J={J1, … Jm} have to be performed on a set of n centers R={R1, …, Rn} (Daouas 1996, Laarhoven et al. 1992). Each job Ji is composed of a set of partially ordered operations op(ij), i= 1, …, m, j=1, …, m(i), where i is the index of the job and j is the index of the step (or the sequential order), m(i) is the total number of elementary operations in a production process. Each operation op(ij) has a deterministic processing time l(ij) and pre-assigned materials M={M1, M2, .., Mk}. The job shop scheduling problem involves synchronization of the completion of m jobs J on n resources R in consuming k materials M, and is one of the most difficult NP complete combinatorial optimization problems.

The problem constraint of job shop scheduling includes:
1. operation temporal precedence, i.e., an operation must be started on after the previous operation in the job sequence (set of operations) should be finished.
2. center capacity constraint, i.e., centers have only a single operation processing capacity.
3. material quantity constraint, that is, corresponding materials must be supplied in stocks before the consumer operation starts.

In principle, the job order has a deadline condition. This condition is considered as a preference rather than a constraint because it is possible to have non optimal solution which satisfies the deadline condition with the other constraints. A solution of a job shop scheduling problem is the set of operations to which is assigned a *start time* (st) and an *end time* (et) which satisfies all problem constraints and satisfies as well the possible the deadline preferences.

### 2.2  Dynamic characteristics and using agents

One of the important dynamic characteristics of the manufacturing is its environmental changes. The system should respond to a sudden change like a new job order, a canceling of a scheduled order or materials' arrival not respecting the scheduled supply time. Another kind of dynamic issue concerns the fact that operations' real finishing time sometimes differ from the scheduled time. In the case of a job shop floor, these dynamic characteristics are not so easy to take into account because of tightly coupled problem constraints. As was noted in (Sauter Parunak 1999), early

scheduling software products were too limited to handle such dynamics or now the software becomes too complex to handle it successfully.

By the characteristics of constructing decentralized complex systems, multi-agent based approaches are often applied to solve the planning and production scheduling problems in industries (Liu Sycara 1996, Muller Parunak 1998). Actually there exist many approaches to tackle the dynamic issues in scheduling systems (Bussman 1998, Daouas 1996) or to solve efficient scheduling problems in job shop (Laarhoven 1992, Liu Sycara 1996). To follow some existing technologies for our application, we have noticed certain limitations.

First of all, the existing researches were carried out with a limited size which is very often not the case of a real industrial application (less than or equal to 30 job order, in (Daouas 1996, Laarhoven 1992) for example).

Secondly, the implementation of a system was based on a simplified context. In (Daouas 1996, Liu Sycara 1996), the authors tackled some dynamic issues in scheduling, or in (Laarhoven 1992) an efficient job shop scheduling problem was addressed, but the supply chain problem was often ignored. Even though some researchers have underlined the importance of the integration of entire dynamic issues in production lines (Sauter Parunak 1999), few applications have realized it in a real context.

And finally, the integration of legacy systems is hardly considered. It is certain that some technical constraints due to the integration may affect the application of a theoretical knowledge and the real implementation. But other experiments rarely mentioned the integration aspect.

Thus we attempted, in our approach,:
a) To realize a combined agent behavior, that is, goal-directed and reactive agent behavior for solving a dynamic scheduling problem for production centers and stocks;
b) To use a stochastic optimization technique like simulated annealing studied by other researchers (Laarhoven 1992) but in the context of different types of agents;
c) To solve the integration problem between a legacy software and the multi-agent system;
d) To test the prototype in an integrated environment with a significant example size.

## 3  DYNAMIC SYSTEM AND OPTIMIZATION PROBLEM

In the context of a job shop scheduling problem, a problem state is represented by an allocation of operations associated to production orders in respecting the constraints related to the operations (temporal precedence, center capacity and material constraints). Dynamic scheduling means finding, starting from the initial state, a new

next state (i.e., allocation of operations) which satisfies the newly given constraints. For the purpose of comparing a new state with the current state, a cost function is used which represents the value of a given state. In this section, we explain the formalization of the cost function and the algorithm of simulated annealing.

## 3.1 Optimization problem and cost function

The cost function is defined over the problem space in which each state represents a complete schedule. The optimization criteria *to minimize* considered in our system are listed below.
1. the number of lately placed orders with a weight parameter (client priority): tardy cost,
2. the total tardiness with a weight parameter,
3. the mean value of each command's tardiness.

Given:
a) nc: the total number of job orders entered into the system,
b) fj: end time of production of a job order j in schedule,
c) dj: given deadline for the order j,
d) Lj: lateness of the job order j (Lj = fj – dj),
e) Tj: effective tardiness of the job order j (Tj = max (0, Lj)),
f) Uj: indicator of lateness of the job order j (0 or 1),
g) Wj: weight parameter for a job order j which depends on the client priority,

four optimization criteria have been formulated as follows:

*Number of job order which are scheduled lately :* $S_{j(1,nc)} Wj * Uj$ ............................(f1)
*Tardiness :* $S_{j(1,nc)} Wj * Tj,$ ............... (f2)
*Mean tardiness : 1/nc \* $S_{j(1,nc)} Tj$* .....(f3)
*Number of non-placed job orders: np (np <= nc in a certain state)* ...............(f4)

Being based on these formulas, the cost function to minimize is given as follows :

$$F = c1*(f1)+c2*(f2)+c3*(f3)+c4*(f4) \quad .........(f5)$$

where c1, c2, c3, c4 are the associated coefficients. In our system, there is a global view point which supervises the cost function.

## 3.2 Simulated annealing

Being based on statistical physics, simulated annealing technique allows to avoid local optima traps which often occur with greedy algorithms. Let F be a cost function to minimize, simulated annealing consists in:
- allowing local cost function deterioration, hoping to improve the global cost function,
- controlling this possibility with a stochastic process which is guided by a parameter, called

the temperature or tolerance. Initially, there is a high tolerance to local cost function deterioration, and progressively this tolerance decreases until the system reaches the equilibrium state (3).

The algorithm of simulated annealing is relatively simple to implement but the efficiency of processing time and the quality of solution are high (Laarhoven 1992). More formally, the probability to accept the state *g* once generated from the current state *c* (Acg) is defined by the following formula,

$$Acg = \begin{cases} 1 \ if \ F(g) \le F(c) \\ 1 \ if \ random[0,1] < e^{\frac{F(g)-F(c)}{T}} \\ 0 \ otherwise \end{cases}$$

where *T* is the temperature at the current state *c*, *F(c)* is the cost function value of current state, *F(g)* is that of a generated state. This formula means that if the newly generated state is better than the old one, the system accepts the new state. If it is not the case, the system accepts the new state with a certain probability. Once the system decides to accept the new state *g*, the system decreases the temperature to adjust it for the new state *g*. Having drawn on the result of (Daouas 1996), the following formula was used to decrease the temperature.

$$T(n+1) = Tn – (0.07 * T(init)),$$

where T(init) is the initial temperature, T(n) is the current temperature and T(n+1) is the modified temperature.

## 4 MODELING WITH AGENTS

The following list shows our model matching between the real world job shop model and the model based on agent.

a) Production order from client → command agent
b) Production center → center agent
c) Stock for materials → stock agent
d) Operation → interaction element between command agents and center agents, managed by command agents
e) Stock movement → interaction element between command agents and stock agents, managed by stock agents

In this model, the assignment of operations results from the interactions between agents which represent the client job orders and production centers, and the plan for stock movements arises from the interactions between agents representing the client job orders and stocks (see figure 1). The center agents and the stock agents are created at the moment of the platform initialization and exist until the platform receives the deletion perturbation

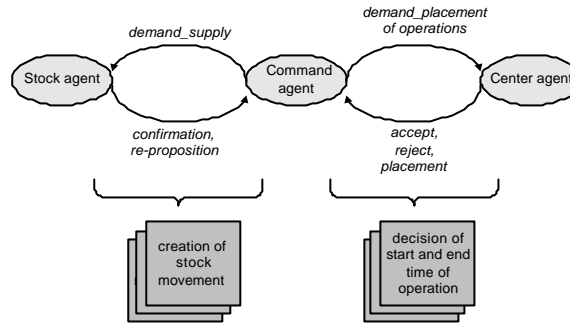of a center or of a stock. We introduce in advance "Operation" and "Stock Movement".



Figure 1: The schedule emerges from the agent interaction.

## 4.1 Operation

The "Operation" element represents an elementary operation. The following information is associated with each operation.

a) Center id : identification of the center on which the operation is executed,
b) Materials : composed of {stock identifier, quantity, duration for new supply},
c) Order relation between operations : previous and next operation,
d) Processing time : duration of execution dependent on the quantity to produce,
e) Temporal information : the earliest, latest and scheduled start time (see below).

Using processing time l(ij) and the deadline Dl, the earliest start time (es) and latest start time (ls) are calculated as:

- The value of es(ij) is equal to:
  *i) the current time unit, if op(ij) is the first operation in production,*
  *ii) es(i, j-1) + l(i, j-1) otherwise, where l(i, j-1) is the precedent operation of op(ij).*

- The value of ls(ij) is equal to:
  *i) the deadline Dl, if op(ij) is the last operation in production,*
  *ii) ls(i, j+1) + l(i, j+1) otherwise, where l(i, j+1) is the next operation of op(ij).*

The interval marked by the earliest and the latest start time mean that if an operation can be started between this time interval, the system guarantees the production deadline. And finally, the real start time is defined by the center agent, in our case, and this means that an operation is scheduled.

## 4.2 Stock movement

In industrial production, the supply chain problem concerns the stock management. Materials are stocked in stocks and consumed at the start time of operations. It is called "stock movement". There are two kinds of stock movement: material

entry into the stock (due to the delivery from suppliers) and material exit from the stock (to supply production processes). "Movement" element type is used to model these aspects with the information: movement identifier, date of stock movement, quantity, stock quantity after movement.

There are also specialized information for each entry and exit type stock movement:

a) Identifier of supplier for material entry: external supplier if the material must be purchased, or another production process if the material is an intermediate product.
b) Identifier of consumer for material exit: the customer if it is a final product, or another production process, i.e., a command agent identifier, which manages the consumer operation.

## 4.3 Command Agent

A command agent represents a production order entered into the scheduling system. It is created when a new job order is entered and works for placing all of its operations on centers respecting the earliest & latest start time range. The necessary information for a command agent is: the production deadline, the priority of the client, a set of "Operations" (see section 4.1) composing the production process.

a) Proactive behavior: A command agent is responsible for calculating temporal information (es, ls) of its operations. Before launching the production planning, a command agent verifies operation by operation the availability of their materials, that is, if the necessary materials can be ready at the "earliest start time". Afterward, it constantly asks to place its operations on centers.

b) Reactive behavior: Various perturbations (modification of the production deadline, insertion/deletion of an operation into/from the production process, receiving a reject notice from a center, or modification of materials) sent from the environment are transmitted to a

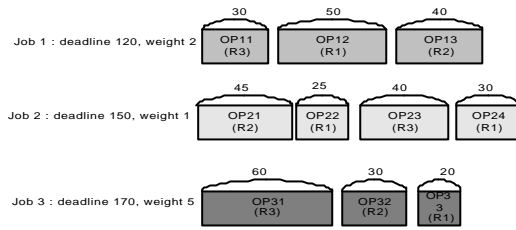command agent. These invoke the associated



Figure 2: Operations for job1, job2 and job3

## 4.4 Center agent

The center agents represent the machines or production centers and work to allocate execution start time of all requested operations without overload. Each center agent keeps: (i) the planned operations in the center, (ii) the available free places to be occupied by operations, (iii) the current simulated annealing temperature.

The experimental results of (Daouas 1996) shows that, by having a separated temperature for each center – distribution of the simulated annealing mechanism – we can speed up significantly the processing time. By the nature of job shop problem, all centers don't have equal occupancy rate for the production of the articles. So it is possible that there are some centers frequently requested for production while other centers are rarely asked for. This characteristic naturally leads us to conceive distributed simulated annealing value for each center.

a) Proactive behavior: none.
b) Reactive behavior: When a center agent receives a 'demand place-operation' message with an operation from a command agent, it searches a free place within his schedule to satisfy the execution of the operation. If there is no more free place, the center agent is obliged to decide whether : i) it rejects another operation to make a place for the new one, or ii) it places the new operation regardless of the temporal values. To take a decision, the center agent uses its simulated annealing temperature to get the acceptance probability presented in section 3.2.

## 4.5 Stock agent

The stock agents are managing materials by maintaining the minimum stock level. The behavior of stock agents generates the stock movement plan including: purchase order, stock movement plan for operation supply:

a) Proactive behavior: During the planning process, it is possible that the remaining stock quantity after movement becomes too short (below the minimum). If a stock agent encounters such a case, it generates a supplying
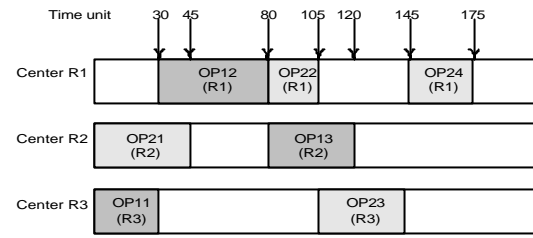
reactive behavior.



Figure 3: Before J3 is entered

order. If the material must be supplied by an external supplier, the stock agent creates a purchase order and then considers it will arrive at the planed time. If the material is produced by internal production, the stock agent creates an internal production order, which must be included in the schedule as a new job order.

b) Reactive behavior: responding to the demand of command agents, the stock agents verify whether the stock level will be enough to supply the necessary quantity of materials. It returns a positive confirmation if it is the case otherwise it re-activates itself for its pro-active behavior.

## 4.6 Agent platform and model of agents' environment

With a view to transferring the technology to the industrial partner and reducing the risk of integration failure, we have developed the agent platform which satisfied only our needs. The main functionality of the platform is:

a) to create and delete the agents and their maintenance,
b) to receive the environmental changes under the form of perturbations,
c) to interpret and deliver the perturbations to an appropriate agent,
d) to request, some supplementary information demanded by the agents and retransmit the information to the environment,
e) and to support all these properties in working with a huge number of agents in the platform.

The last element is mandatory in viewing the real problem size of industry's databases. In an extreme case, there are more than 100 centers and 5000 materials used, and some hundreds of job orders to be planned. As a result, huge number of agents in execution. We implemented the platform to activate each agent (implemented in Java object) in some order with the serialization of the agents on disk. This enables us to integrate the system with a large size of legacy database.

In our system, the agents reside in an environment which produces the changes representing the user's input. The changes called *perturbations* transmitted from the environment.
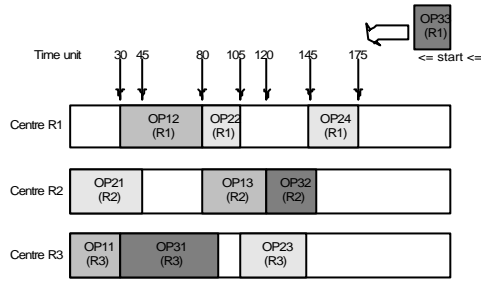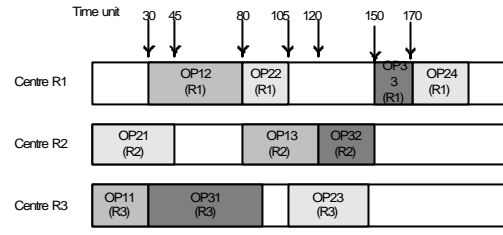
Figure 4: During scheduling J3



Figure 5: Final state

Between the legacy system and the multi-agent system (MAS) there is a software kernel, developed by the other partner (Icare/IsNet), to transmit the user's input conditions. We call it "Business Object Kernel (BOK,)". Total 37 perturbations arrive to the MAS platform via BOK. These perturbations are transformed into appropriate agent messages for the purpose of activating agents. The perturbation arrived to an agent is then propagated between different kind of agents via agent communication until there will be no more modification considered.

# 5   SIMPLE EXAMPLE

In this section a simple example is presented to show how the time value information associated to operations is used during agent interaction and with the agent messages. In this example, a relative unit time value in integer (0, 1, 2, … ) is used, but in the real prototype system real time values (year, date and time) are used in minute precision.

The example is composed of three production centers (R1, R2, R3) and three job orders entered into the system in sequence. The coefficient parameters are all set to one. On the center agents, there are two jobs already scheduled, J1, J2 like the configuration in figure 3. At a given time, the state of command agent for J1 (represented by agent CA1) and the command agent for J2 (CA2) are stable, that is, all their operations are placed on center agents (figure 3). The global cost function value is: F(c) = 0.

We imagine that a new J3 is arriving with the given information in figure 2. Just after that J3 is entered into the system, the cost function value is modified by the following calculation:

$$F(c) = 0 + 0 + 0 + 1 = 1$$

For the simplicity, we do not detail, in this example, the interaction between command agents and stock agents. Now we follow the agents' behavior step by step. Start of the command agent's behavior

## 5.1   Start of the command agent's behavior

CA3 calculates the necessary information of operations:

- OP31 : earliest start time es(31) = 0, latest start time ls(31) = ls(32) – l(31) = 120-60=60
- OP32 : es(32) = es(31) + l(31) = 0+60=60, ls(32) = ls(33) – l(32) = 150-30=120
- OP33 : es(33) = es(32) + l(32) = 60+30=90, ls(33) = 160 – l(33) = 150

Before to start the conversation for the purpose of placing its operations on the centers, agent CA3 communicates with stock agents to assure the necessary quantity of materials at the calculated earliest start times. We imagine that there are sufficient materials in stocks so that the temporal values for es(31), es(32) and es(33) are confirmed.

## 5.2   Placing the operations

CA3 contacts the R3 to place the OP31. R3 finds a place (0<30<60) for OP31 and it accepts OP31. CA3 continues to demand for the OP32 after having modified its temporal values, es(32) to 90 (60 + 30 = 90). For the two first operations, there are suitable places and these operations are accepted by the center agents (figure 5).

But when CA3 demands the placement of OP33, R1 notes that the place starting from and ending with time unit 150 is already occupied by another operation OP24 (from 145 to 175). So the agent must decide whether it rejects the operation OP24 and put OP33 in the place (late execution of OP24), or it places OP33 after the operation OP24 (late execution of OP33). It uses the simulated annealing value with the associated local temperature and the global cost function to take a decision. In this example, the cost function value of current state F(c) is equal to 0. And then, the next possible state is described as follows:

- Center R3 rejects op24 and accepts op33.
- Because of op24 being rejected, CA2 becomes not placed so that the value for function f4 in section 3.2 is changed.

Thus the new cost function for a generated state F(g) is :

$$F(g) = 0 + 0 + 0 + 1 = 1$$

R3 applies the simulated annealing formula in section 3.1 ($F(g) <= F(c)$) and places Op31 in rejecting Op24. By the result, the command agent CA2 is re-activated to satisfy its goal, i.e., place the operations. The figure 5 shows a possible finale state.

# 6 EXPERIMENTATION

We have experimented the multi-agent system with randomly generated examples. The purpose of the experimentation was:
a) To justify the application of simulated annealing method in complex job shop environment,
b) To verify whether the processing time is acceptable in real world execution.

The original database that we used has been supplied by the industrial participant (TI Informatique). It contains the necessary information concerning the production processes and materials of each unit operation. We have used only one type of final product which is composed of 10 elementary operations and which needs an intermediary article composed of 6 elementary operations. The number of production centers is fixed to 6.

We have considered only the production job orders. Other dynamic aspects of the system, for example, the comparison of processing time of different types of perturbations, is excluded from this experimentation.

## 6.1 Parameter used in random generation

Being based on (Daouas 1996) we have varied: (i) the number of production job orders, (ii) the difficulty of the generated problem.

To decide the number of production order, we have referred the statistical analysis results carried out among the users of VisualProd system. The result shows that there are 44 production orders entered into the system and 10 productions finished daily. Approximately, we have tested the system with maximum number of 100 commands. This already overpasses the number of job orders tested by other researchers.

We used a random function to generate the production deadline using the following formula to vary the problem complexity by controlling the deadline:

$$Dl(j) = Du(j) + Du(mean) * g(\alpha) * nd,$$

where $Dl(j)$ is the production deadline of the job order j, $Du(j)$ is an approximate duration of the job order j, $Du(mean)$ is an approximate duration to produce 50 final products, $nd$ is the number of job

orders, $g(\alpha)$ is a randomly generated number between ($\alpha$-0.1, $\alpha$+0.1).

We also generated at random the quantity of product, for each production order, between 1 and 100 (according to a uniform distribution) and measured the scheduling time in millisecond. We varied certain parameters: (i) the number of production order varies between {10, 20, 30, 40, 50, 100}, (ii) $\alpha$: {0.5, 1}. We have executed 5 times with the same example - that is, same number of command, same degree of difficulty, randomly generated quantity of product - to get an average value.

## 6.2 Results and Discussion

We have tested the first implementation version of our system with the number of production orders 10, 30, and 50, and the initial stock level set to zero. Unfortunately, the result has been away from our expectation (see table1) in measuring the processing time.

One of the benefits of applying simulated annealing method is its linear increase concerning the processing time. But in our case, the processing time has increased exponentially in proportion to the number of job order. We have analyzed the reason like follows:
a) The problem context becomes much more complex by integrating the stock management which was not the case in (Daouas 1996, Laarhoven 1992). By the result, the interaction between command agents and stock agents becomes complex.
b) In our case, the problem size is more important that the others. Most of the experimentation has been executed over smaller problem space composed in more or less than 30 job orders. If we reduce our problem size like those, we show no more serious growth of processing time but the exponential increase is remarkable after processing of 30 job orders.

After our first trial, we have modified certain system properties, in reserving the important principals, so as to reduce the exponential growth curve. The modifications are:
a) Limitation of the maximum number of rejection per operation in centers;
b) Modification of agent communication scheme. We have limited the pure agent message send/ receive. Some parts of agent communication were replaced by a blocked transaction using direct message passing between agent.
c) For concentrating on the processing time evaluation between center agents and command agents, we have taken a sufficiently high initial stock level.

The table2 show the result after the modification:

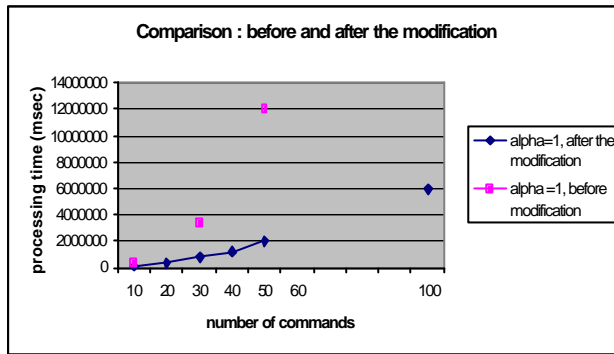a) the growth of processing time is in linear increase, and
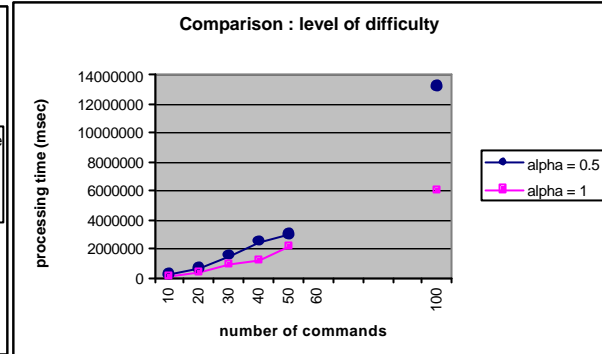
Table 1: First experimentation



Table 2: After some modifications

b) the processing time of a hard problem ($\alpha = 0.5$) is superior to the less difficult one ($\alpha = 1$).

# 7 CONCLUSIONS

As was mentioned in (Parunak 1999), an industrial system is a mean to an end and will be accepted only if the firm can justify the project cost against expected benefits. Although the characteristics of multi-agent and distributed agent systems promise their applicability for modular, decentralized, complex and changeable enterprise systems, there are always the problems of legacy system integration and of performance.

We have succeeded to replace the existing scheduling module using agents' interaction to integrate dynamic scheduling. Now, the users can consult the impact of their input concerning new job orders, modifications of certain conditions, information for stock movements. The solution shows the new production schedule on the centers, what materials must be purchased, what production orders are retained, etc., which was exactly what the industries wanted. With our case example in the previous section, the processing time for re-scheduling after receiving a perturbation is about 5 –10 minutes. Meanwhile, if the system is used in a complex problem space, that is, scheduling of operations with the stock movement planing like in our system, it is possible that the processing time increases exponentially in proportion to the number of job orders and the stock state.

Now TI-Informatique continues to integrate the prototype into the other parties of VisualProd so as to get a new upgraded version. One of major duties during this integration phase is to adjust simulated annealing parameters which will pertinent with different size and characteristics of database.

# REFERENCES

Stefan Bussmann, An agent-oriented architecture for holonic manufacturing control, First International Workshop on Intelligent Manufacturing Systems, 1998.

Thouraya Daouas, Ordonnancement distribué réactif pour un atelier d'assemblage de type flow shop, Doctoral thesis, Neuchâtel university, Suisse 1996

Daouas, T., K. Ghedira, J.-P. Muller, A distributed approach for the flow shop scheduling problem. Third International Conference on Artificial Intelligence Applications, 1995.

ICARE-IsNet, http://www.icare.ch/

Peter J.M.Van Laarhoven, Emile H. L. Aarts, Jan K. Lenstra, Job Shop Scheduling by Simulated Annealing, Operations Research, volume 40, pp 113-125, 1992.

Jyi-Shane Liu, Katia P. Sycara, Multiagent Coordination in Tightly coupled Task Scheduling, Second International Conference on Multi-Agent Systems, 1996.

L. Monostori, J. Hornyak, B. Kadar, Novel approaches to production planning and control, First International Workshop on Intelligent Manufacturing Systems, Switzerland, 1998.

Jean-Pierre Müller, Vers une méthodologie de conception de systèmes multi-agents de résolution de problèmes par émergence, JFIADSMA'98, Hermès.

Jean-Pierre Muller. H. Van Dyke Parunak, Multi-agent systems and manufacturing, 9th Symposium on Information Control in Manufacturing INCOM98, France, 1998.

H. Van Dyke Parunak, Industrial and practical applications of DAI, In (Weiss 1999)

John A. Sauter, H. Van Dyke Parunak, ANTS in the Supply Chain, Workshop on Agent Based Decision Support for Managing the Internet-Enabled Supply Chain, Agents99, 1999.

Visual Prod, http://www.ti-informatique.com/

G. Weiss (editor), Multi-agent Systems, MIT Press Cambridge MA, 1999.

# Acknowledgments