A Multi-Objective Genetic Algorithm in Job-Shop Scheduling Problem to Refine an Agents' Architecture

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Abstract

Determining an optimal solution is almost impossible [2] but trying to improve an existing solution is a way to lead to a better scheduling. By crossover and mutation of agents, according to their fitness function, we improve an existing solution.
So, determining a good and valid solution in a Job-Shop scheduling problem mustn't be the optimization of one criteria. To do that, we use a Multi-Objective Genetic Algorithm to find a balance point in the respect of a solution of the Pareto front. Of course, this solution isn't the best but allows a multi-criteria optimization.
In a second time, we present the benchmarks' results that have been done on a SGI Origin 2000. The interpretation of these, is a way to refine heuristics given by our evolution process and a way to constraint our agents based on a contract net system.

1 INTRODUCTION

In Job-Shop Scheduling Problem (JSSP), Gantt diagram's optimisation can be considered as NP-Difficult problem [2]. Determining an optimal solution is almost impossible, but trying to improve a present solution is the way to lead to a better tasks repartition. Thus, we use Multi-agent Systems (M.A.S.) [4]. It simulates the behaviour of entities that are going to collaborate to accomplish actions on the Gantt diagram so as to resolve a given economic function. The ideal solution of this problem is a point where each objective function corresponds to the best (minimum) possible value. The ideal solution, in most cases, does not exist because of the contradictory nature, rather contradictory objective functions: compromises have to be done.

2 INFORMATION SYSTEMS FOR MANAGEMENT USING A MULTI-OBJECTIVE GENETIC ALGORITHM

2.1 Agents Evolution

Multi-agent systems include cognitive agents whose the behaviour tends to satisfy one or some objectives taking into account some constraints of facilities and their proper expertises. Normally, agent creation is simply based on cloning. Thus, it is possible for agents that provided or done good actions, that they could give birth to individuals whose characteristics would be superior by crossing. So, we use the notion of evolution, by introducing evolutionary algorithms such as Multi-Objective Genetic Algorithms that simulate a Darwinian process [7] (Fig. 2).

Consequently, we propose to put in evidence the use of spirit of Genetic Algorithms [5] into evolution in a M.A.S. We plan to focus on the possible relationships between MAS and GA in order to define a new property of agents, and more generally, of MAS: the notion of sexued reproduction.

In our case, it is necessary for us to optimize a Gantt diagram [10]. It is necessary to minimize the delay and the advance of the set of jobs. The objective with an advance and a null delay is nearly impossible. We must calculate the fitness of an agent, that is to say its impact on the Gantt. Of course, for the set of jobs, we can have a delay or a weak advance. Consequently, we haven't a fitness function but many. We have as many objectives as we have jobs. So why, we have a case of "multi-objective genetic algorithm". The ideal solution of this problem is a point where each objective function corresponds to the best (minimum) possible value. The ideal solution, in most cases, does not exist because of the contradictory nature, rather contradictory objective functions: compromises have to be done. Solving a multi-objective problem [3] requires the identification of Pareto optimal solutions.

As said previously, the ideal solution, in most cases, does not exist because of the contradictory nature, rather contradictory objective functions: compromises have to be done. A different concept of optimality has to be introduced. Solving a multi-objective problem generally requires the identification of Pareto optimal solutions [8], a concept introduced by V. Pareto, a prominent Italian economist, at the end of the last century. A solution is said Pareto optimal, or non dominated, if starting from that point in the design space, the value of any of the objective functions cannot be improved without deteriorating at least one of the others.

2.2 Agents Granularity from Multi-Objective Genetic Algorithm

During the optimization process, mutations and crossovers of agents give new agents (Fig. 1) with different granularities. The agents of the M.A.S. can be:

- Local agents whose actions result of "simple" heuristics on a well known task (permutation of tasks in case of due date, measure of the algebraic tardiness of a task, etc.).

- Global agents whose actions are the result of heuristics, more global that can be extracted from Gantt diagram (too many holes, a lot of job which are late, etc.) referring to areas. These agents have an a priori knowledge of the environment, they can determine a quality for our diagram: good, worst, ...

Therefore, global agents contain meta-heuristics corresponding to actions to consider according to the resources that agents have from the Gantt diagram; local agents own *"simple"* or *"combined"* actions heuristics. The problem is to bridge the gap between actions of local agents (local heuristics) and global agents (global heuristics). During the cooperation process of agents, they are developed and left their marks on the environment. The resolution of our optimization problem is done by an agent's evolution. This evolution can be obtained from different ways:

- a mutation of the behaviour of some agents, these being obtained by evolutionary algorithm,

- a set of agents inducing the emergence of agents of intermediate granularities (intermediate heuristics) between local agents and global agents.

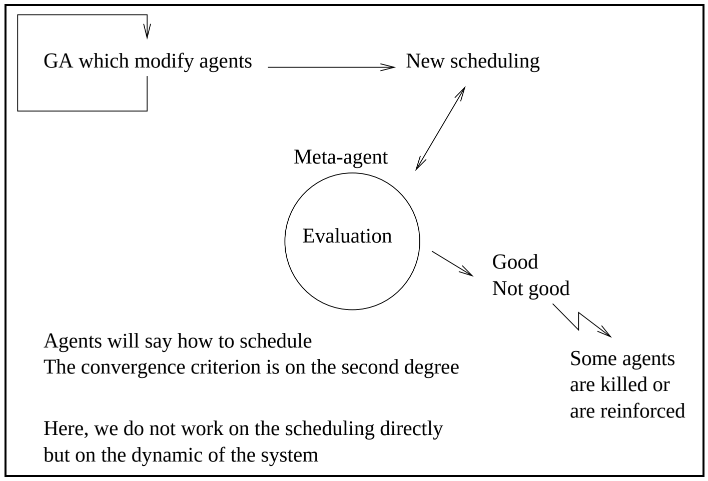

Figure 1: GA modify agents' environment

Thus, we will end at the creation of agent of intermediate granularities proceeding roundups of local agent to form global agents or being over subtle global agents to obtain quasi minimal agents. However, this mutation of the behaviour does not have to be made in totally random manner, it must take different communications into account that can exist. Therefore, this mutation will have to correspond to a character or to an emergent tendency of the action of agents. This agents reproduction by evolutionary algorithm will not have to take crossover from two parents into account but from two or more parents. The crossbreeding will not have to take local functions of agents into account but senses resulting from the agregation of agents in a group with a group action function. Consequently, new agents, with an intermediate granularity, will have functions resulting from parents but, they will have senses, tendencies and news visions for actions to accomplish on the Gantt. Communications between global and local agents, due to their actions, manage the appearance of agents with an intermediate granularity and the global optimization in Job-Shop Scheduling Problems. Therefore, the construction of some system simulating living organisms or social systems, cannot be modelled using a stricly mechanical approach. These systems are typically adaptive and their behaviour is no regular. Their conception entails to take into account the notion of no regular organisations. Conception is based on the agent paradigm, setting the problem to the level of the organizational definition of the agent concept, which is not only functional. Then, the multi-agent system must express radical characters, such as reification of emergence, property of controlled self-reproduction of groups of agents and no linear behaviour.

3 ROUNDUP OF ENTITIES FOR TRAINING PACKAGES IN A MULTI-AGENT SYSTEM

In production management, manipulated entities are batchs, operations, machines, etc. In essence, the optimization in production management consists in determine a proper location for the operations set by respecting the different constraints (resources, precedence constraints, etc). Consequently, this kind of problems is NP-Difficult typically, that is to say that we can not determine an optimal solution in a reasonable time. Therefore, determining an optimal solution is a quasi impossible process. Therefore, the goal is to find

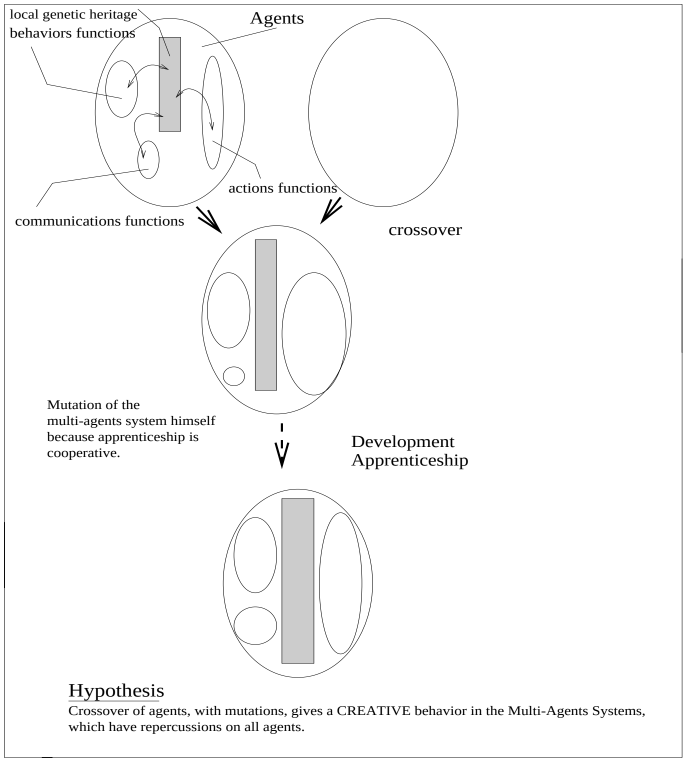

Figure 2: Crossover between agents using the spirit of GA

a point of balance corresponding to a good solution and respecting the set of constraints that the user has fixed.

As we come to signal it, it is highly likely to find a solution to a scheduling problem and especially to a Job-Shop Scheduling Problem. Thus, we will seek to improve an existing solution by manipulating objects on a Gantt diagram by the use of a Multi-Agent System piloted by a Multi-Objective Genetic Algorithm.

Objects manipulated on the Gantt diagram are static objects essentially (batchs, operations, machines, etc) that we attempt to arrange to the most relevant way. Each entity has a value of performance as compared to its objective (delay, advance, etc.). In order that, the Multi-Objective Genetic Algorithm intervenes directly on entities by operating an objects reification so as to obtain packages. The roundup (package) allows to realize an economy on times of cleaning and meadow-series in computing the costs matric again. Nevertheless, the Multi-Objective Genetic Algorithm can not realize the set of packages, this is why, we use a Multi-Agent System. The goal is to realize aggregations of basic entities to arrive to an unique entity that is the Gantt diagram at the end. In essence, this aggregation takes to a granularity of entities. These roundups are operated by groups agents and by "social" agents whose function is to organize the space of the Gantt diagram.

Therefore, the agent has a bulking function essentially. This operation uses a prey/predator system seeking to improve packages by destroying the bad groupings to distribute them in others. However, these groups do not constitute a partition but groups having a senses. More, these packages can overlap to enrich their contacts network and to develop strategies for the global improvement of the Gantt diagram.

Roundups do not form a partition of the space of the Gantt diagram, to make this, agents with aggregation tendencies are used that define a structure and or an effective contacts network so as to promote the global improvement of a solution corresponding to a Gantt diagram. Thus, it is possible to energize our system and by extension our problem by replacing the worst packages by the most effective. In this way, an alteration of groups is done at the crossovers level breeding by Multi-Objective Genetic Algorithm just as agents crossover making the MAS to obtain individuals with behaviours and different tendencies.

3.1 Macrophagic Agents to Protect the MAS from a Chaotic System

By mutations and crossovers, agents will be metamorphosed into entities with different granularities. Therefore, these new agents haven't necesseraly capacities to resolve our problem. They have like capacity to tumble the system. Then, this one begins chaotic. Thus, for each agent, a fitness value is associated. Then, the "worst" agents correspond to "parasites" that macrophagic agents cut to reduce them into elementary elements, kind of nucleotides, which the function is to bring into play elementary heuristics (delay's calculus, move a tardiness operation, etc). Consequently, our macrophagic agents have as main objective to reduce the number of agents by digesting these that do not be of use to the system and these that return a chaotic system. By giving elementary agents, macrophagic agents provide basic units for the evolution of "organizing" agents for our problem. Macrophagic agents is a Multi-Agent Sub-System because they correspond to a defence entity against stresses that may appear on the Gantt diagram. We simulate a kind of immunological defences against agents that create chaos. Then, the Multi-Agent System can improve the Gantt diagram.

4 GOING DEEPLY IN THE RELATIONSHIPS OF GA AND MAS

The use of GA in MAS is the beginning of what can be an interesting research area. There are clearly two kind of approaches, the first is centralized, in other words, some of the genetic is outside the agent. The function of selection is a good example of such out-of-the-agent feature [10].

However, we believe that if one wants to completely merge the genetic approach and MAS, we must make the agent a completely autonomous genetic entity. By that we mean that not only the genetic patrimony has to be "onboard" but also the functions of selection and crossing. An agent must choose which other agent it wants to reproduce with [10]. The location of the function of mutation is not clearly known since it is caused by the possible exposure to external events coming from the environment and during the genetic code replication phase. If we also introduce the notion of motivated behaviour for agents [1] we go deeply in the artificial life problematics. The genetic autonomy and the notion of motivation for an agent may lead to a drastically new kind of emergence phenomenon (different social behavior, auto-refering evaluation process, ...) in self-organizing multi-agent systems. It is certainly a difficult task but it may set the seeds of a prolific approach concerning artificial life.

5 OBJECTIVE OF THE MAS ON THE GANTT DIAGRAM

By definition, MAS represent a subset emerging of the artificial Intelligence that tend to put in evidence the two following principles:

- The complex system construction employing agent multiple,
- Mechanisms for the co-ordination of independent agent behaviours.

Nevertheless, this definition is not generally accepted in AI, for purposes contained in our article, we consider an agent as being an entity with objectives, actions to accomplish and areas of knowledge, which is situated in its environment. However, the ability to consider the co-ordination of the autonomous agent behaviour is a new way among fields of the Distributed Artificial Intelligence (DAI).

Therefore, because of the knowledge of agents, rules of actions, ..., the MAS will have for principal objective to group agents having similar behaviours to elaborate strategies to the jobs level, jobs of jobs, machines, machines of machines, etc. Thus, it appears the notion of group. The objective of the MAS is to improve the Gantt diagram, therefore it invites to establish the notion of group corresponding to elementary entities having common grinds and physical sameness (same capacity of machine, etc.) or interdependence.

We will use the notion of zone for the roundup of entities on the Gantt diagram while we will speak about the notion of group for the roundup of entities similarly or close nature. Agents have to intervene on groups and elementary entities, the MAS will be then composed with micro and meta-agents. It is therefore important, for this evolution, to introduce agents having a character: the meta-agents of evolution. These meta-agents will have therefore as function to make evolve this organization by means a Genetic Algorithm establishing the sexued reproduction of agents. It is necessary to note that, traditionally, agents have as unique possibility only the cloning. But here, we use Genetic Algorithm for the physical evolution of agents. It appears therefore, in the course of the evolution, different sizes of agents: we will speak about agent's granularity. We have therefore micro and the meta-agents that are going to intervene, according to their size, on an entity or a group, by passing by intermediate levels. Thus, agents having a meta-knowledge are going be able to intervene on the macro-entities (group) as well as on some zones of the Gantt diagram. It appears therefore a distributed agent system being able to mutate and cross between them.

6 RESULTS FROM GENETIC ALGORITHM

6.1 The fitness function

In our case, it is necessary for us to optimize a Gantt diagram. Therefore, the last operation to undertake will have to correspond to the date of end minus the time of the task. It is necessary, therefore, to minimize the delay and the advance of the set of jobs.
The objective with an advance and a null delay is nearly impossible. In a general manner, we allow a certain delay or advance. Calculate the fitness of an agent, that is to say its impact on the Gantt. Of course, for the set of jobs, we can have a delay or a weak advance. Consequently, we no longer have a fitness function but many. We have as many objectives as we have jobs. Consequently, we have a case of "multi-objectives genetic algorithm". For this type of problems, we will use the basic concepts of the Multiobjective Optimization Problem (MOP).

6.2 Results

From our object modelisation, a genetic algorithm using the placing method has been developped [6]. This program uses the C++ language in order to use it on a SGI Origin 2000. Here are some benchmarks (See fig. 4). As the calculation time depends on the load

Nb. of jobs	Nb. of operations	Nb. of machines	Calculation time
10	10	4	50sec.
50	5	4	9 min. 53 sec.
50	10	4	14 min. 27 sec.
100	10	10	40 min. 58 sec.
500	100	50	2 h. 24 min. 07 sec.

Figure 3: Benchmark's results.

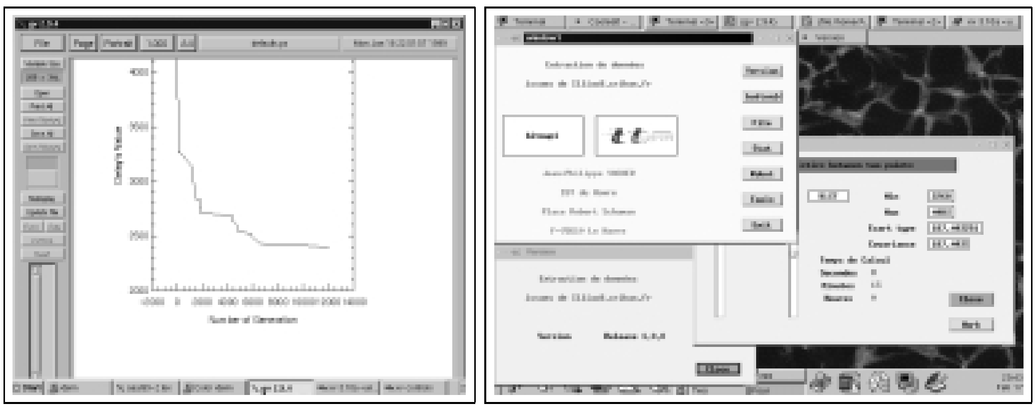

Figure 4: Tardiness' evolution and heuristics extraction programs

of the computer, this time doesn't correspond to the CPU time. We can then determine heuristics to use with our dynamic model based on the contract-net protocol [9]. An other result coming from the simulation process is a set of graph giving the tardiness in function of the number of generations. We can see that the delay decreases rapidly. But it is not necesary to increase the number of generations to obtain a better result (Fig. 5).

6.3 Encountered problems

In our problem, the first level of modelisation was a static model. This one doesn't take into account the fact that we have interactions between machines and jobs. A job can be done only if the resource is free. On the other hand, the static model doesn't include the possible interaction between the workshop and the environment such as a strike, a machine failure, etc. In the static model, the placing obtained gives a solution corresponding to the schedule of all jobs. But, by negociations, the schedule can be built step by step. For example, if a job arrives too soon, the delay corresponding to the tardiness increase. Therefore, if we can change the schedule during the calculation process, we can improve the tardiness. It is one of our economic functions.

7 CONCLUSION

Determining an optimal solution is almost impossible, but trying to improve an existent solution is the way to lead to a tasks repartition which is better. Therefore, we use have used Multi-Agents Systems. We have seen in this draft that a Multi-Agent System can be used with a Multi-Objective Genetic Algorithm to minimize an economic function

corresponding to some criterias for our Job-Shop Scheduling Problem.
During the simulation process, agents granularity appears with the mutation behaviour introduce by GA. At the end of the simulation, communications between global and local agents, due to their actions, manage the appearance of agents of intermediate granularity and the global optimization in production scheduling.
This communication reflects the genetic integration in a multiagent system; the first results show that a MAS and a multi-objective GA are a way to optimize a Gantt diagram of a Job-Shop Scheduling Problem.

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