Intelligent Work Allocation Modeling on a Hardmetal Production Plant

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Abstract – **Allocation problems are one of main problem targets to apply today's agent based computing. They can be found in a large specter domains ranging from production task scheduling to resource allocation or distribution problems. However, there are cases where agents, even being autonomous, do not decide what to do without human intervention and decision. Most of these cases are concerning with economic aspects. If we have a scenario where decision making is inherently decentralized and the agents - with the ability to act rationally - must to deal with resource allocation problems, it is possible to integrate economic principles in such kind of problems. This paper presents and describes the work related to the application of economic decision approaches to a hardmetal production simulation system. Such process provided a new model where system's agents have the ability to control intelligently work allocation in each production stage, improve cooperation among production agents, and optimize overall system performance.**

I. INTRODUCTION

Nowadays an enterprise to be competitive and successful on the market must have flexible production means, high qualified personnel, modern facilities, and efficient work allocation mechanisms. Product quality and commercial viability are largely affected by the availability, adequability, qualification and motivation of the work teams, plant resources involved with the productive processes of an enterprise. Furthermore, the diversity of the production lines, that we may find in a modern enterprise plant, and the commercial position occupied by its products in the market, act as primer factors in the certification process of the enterprise.

The achievement of these goals can be simplified through the application of *Artificial Intelligence* (AI) techniques and, in particular, by the Expert Systems ones [9]. The significant increment of the productive processes complexity and the demand of high quality products and shorter productive cycles are relevant factors that show the inadequability of some of the conventional production techniques to the actual market demands. Such factors may be critical if an enterprise works accordingly the specific product needs of the clients. This generates frequently new product specifications and, consequently, new production plans and sometimes new working methods. AI can help significantly in the integration of flexible production strategies and better resource allocation and optimization methods in the enterprise's decision and production planning abilities. This contributes significantly to a more flexible and effective production system plant, allowing to answer more conveniently to client demands.

Additionally, the use of techniques developed in the *Multi-Agent Systems* (MAS) field can facilitate production systems' behavior analysis. The modular approach provided by MAS combined with the aptness that agents have to emulate the expertise and knowledge of human experts, potentates the development of sophisticated and flexible control systems for an enterprise production plant. Based on these ideas a distributed MAS oriented to the simulation of the management and control of a specific production system of hardmetal products was developed.

II. THE HARDMETAL PRODUCTION PLANT TESTBED

In order to test and analyze the behavior of a distribute MAS environment - The BeAble System [5] - a set of four testbed were developed. One of them was related to a simulation system of a hardmetal production plant [4]. Some of the main reasons that supported the development of this testbed were concerned with the verification of the effectiveness of the system's control mechanisms in situations of deadlock and contention generated by conflict situations among the system's agents, the study of the general dynamics of the overall production system, and the testing of some global coordination models in a system based on agents oriented by tasks.

The system simulates the "behavior" of a group of autonomous agents that manage and control critical points during the main production phases of a specific range of hardmetal tools and products. System's agents are opportunistic entities that work together, developing cooperative activities, in order to optimize and improve the overall production performance of the plant. The system considers several groups of agents with different knowledge and skills, containing each of them at least one agent. They were developed and distributed according to the main system's activities that we considered important to simulate: production orders preparation, raw materials preparation, pressing, machining, sintering, physical control, grinding, final control, packing and shipment, and monitoring.

According to the real production system, agents are located in specific production points, acting as machine supervisors and managers of their tasks. In each agent we integrated the expertise and the knowledge needed to simulate the behavior of each machine during the realization of their main tasks.

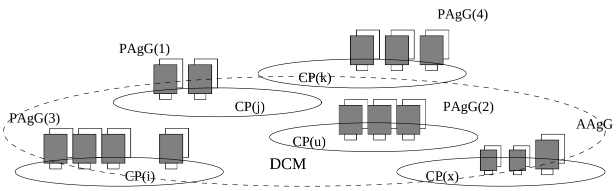

Figure 1. The Agent Based Production System Model.

Figure 1. presents a general overview of the production system. Agents, independently from their classes and work abilities, may be located in distinct computational platforms (CP(1..n)) - which allows to reflect the distributed nature of the productive resources - each of them connected to the system's distributed communication medium (DCM). In a single CP we may locate a community of production agents (PAg(1..m)) responsible to execute one or more operational tasks in the production of the hardmetal tools. All the production agents coordinate their tasks through message passing, using the DCM as a privileged medium and as a way to support temporary data and knowledge related to productive activities. The last group (AAgG) is constituted by three agents that are responsible to do administrative and support tasks in the system. They perform main operational systems tasks - system initialization, agent's activities observation and maintenance of the distributed communication medium -, and perform global system surveillance tasks.

The opportunistic behavior presented by agents during the production stages simulation of the hardmetal pieces allows them to act over a specific production order without previous assignment, decide autonomously about what kind of tool they must to use, or even select the better method of work to apply in their current production tasks. However, such kind of behavior may lead, in some cases, to an unbalanced production plant, where some agents work more than others. This situation may be caused by different characteristics that agents may have, concerning skills and knowledge.

Additionally, different agents have different kind of resources that can use on their work, which provokes *per se* different forms of behavior and, eventually, different performances for the same products. Moreover, if we need to modify the priority of a specific production order, then we must interact directly with the agents, trying to communicate what kind of work they must do in a particular moment. In such a way, we limit the agent's aptness to act autonomously and impose dependence of human control, what is not desired in any intelligent MAS. So, in order to solve these difficulties, we adjusted the previous model of the system designing inside each production phase an intelligent allocation agent that uses economic decision approaches conciliated with the ones related to contract net protocols.

III. ECONOMIC BASED APPROACHES

Wellman argues that it is possible to apply economic principles to solve almost any problem where the following conditions hold [11]:

- the fundamental problem to be solved is one of resource allocation;
- all the involved agents act rationally in order to achieve their most preferred outcomes;
- the decision making is inherently decentralized.

In the task allocation problem of each production stage all these conditions hold. If a large set of tasks must be executed by a limited set of machines it is necessary to decide how their production capability (the available resources) will be allocated among the tasks. Both the agents in control of the machines and the agent in charge of the production stage must act rationally in order to achieve their objectives: the former ones try to reduce their operation costs while the later wants to minimize the total cost of executing its parts of the production orders. The later condition holds trivially since each machine in each production stage is controlled by an independent agent and different agents exist to control the different production stages.

The protocol that supports the negotiation process between the agents is the *Contract Net Protocol* (CNP) [8, 3]. This protocol reproduces, in a precise manner, the interactions that occur in real markets when an entity wants to determine the best partner to execute a particular task. Two roles coexist in this protocol:

- the *managers*, that announce the tasks that must be allocated and select the best candidates for their execution;
- the *contractors*, that answer to the announces with a bid that reflects their suitability to the execution

of the tasks in the hope that eventually they will be selected to execute them.

The economic principles are applied in the decisions that must be made in the *announcing*, *bidding* and *awarding* phases of the CNP. The approach followed in modeling these decisions is a restriction of our previous work in the area of resource allocation in multi-enterprise environments [2, 1], which in turn was based of Sandholm work in the area of automated contracting using extensions of the CNP [6, 7].

IV. THE SYSTEM'S ECONOMIC MODEL

The system framework is composed by several groups of agents, each one associated with a specific production stage. Each of this groups has two types of agents:

- *Allocation Agents.* Each production stage has an allocation agent that acts as a manager in the instance of the CNP used to allocate the tasks in that stage. They are responsible by the announcing and awarding phases of the protocol.

- *Production Agents.* They act as machine supervisors and assume the role of contractors in the CNP. Every time the allocation agents announce a new task, they propose the best bid they can according to their actual schedule and the capabilities of the machine they supervise. This bid is determined based on marginal cost calculations.

An illustration of the CNP phases for this particular setting is presented in Figure 2..

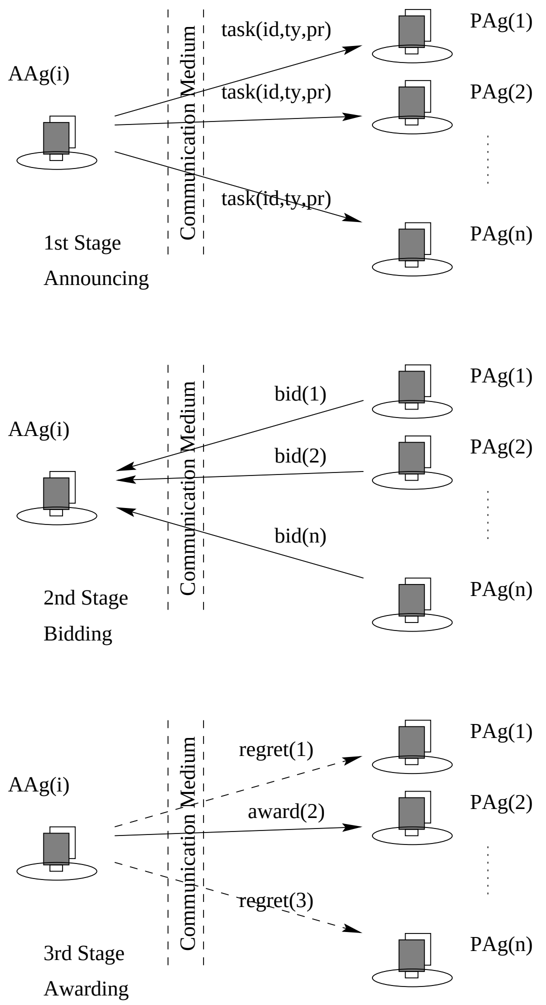

Figure 2. Illustration of the Contract Net Protocol.

The announce of a task t must specify its type ($type(t)$), the priority assigned to its execution ($prio(t)$), and the time instant of its arrival to the production stage ($created(t)$). In order to determine the best bid to submit to the allocation agent, each production agent must have the knowledge to determine the duration time to execute a particular type of task in the machine it controls ($duration(type(t))$), and cost per time unit of operating that machine ($cost/time$). It must also have a local optimizer module that determines the best execution plan to a given set of tasks T, denoted as $best\_plan(T)$. The best execution plan p is the one that minimizes the cost of executing all of its tasks. The proposed negotiation mechanism is independent of the type of optimizer used and it is possible that different optimization strategies are used in different production agents.

Although different optimizers can be used, the process of determining the total cost of executing a plan is well defined, so that it reflects the priority assigned to the tasks. Let $tasks(p)$ denote the set of tasks included in plan p. Then the cost of executing a plan is determined as

$$\sum_{t \in tasks(p)} duration(type(t)) \times cost/time + cost(t,p)$$

where $cost(t,p)$ denotes the variable cost of executing a task t in a plan p. This cost is determined as

$$cost(t,p) = (begin(t,p) - created(t)) \times prio(t)$$

where $begin(t,p)$ denotes the time instant when task t is scheduled to begin execution on plan p. In the variable cost equation the task priority is included as a cost factor that is proportional to the time needed to initiate the task.

This approach transparently influences the local optimizer in order that it schedules first tasks with higher priority. Besides reducing the problem of scheduling tasks with priority to the more simple one of scheduling without priorities, with this approach the parameter $prio(t)$ is not, as usually, a meaningless integer that as little correspondence with a real parameter, but a delay cost per time unit, which is a factor that enterprise managers are used to deal with.

If each task is allocated in turn, i.e., the CNP is run into completion for each of the tasks that are in the arrival queue of the allocation agent, then the bid that a production agent should submit is determined as the marginal cost of adding the announced task t to the current set of scheduled tasks T:

$$bid(t) = cost(best\_plan(T \cup \{t\})) - cost(best\_plan(T)) \quad (1)$$

If concurrent negotiation of multiple tasks is allowed, the throughput of the production stage can be drastically improved. However, to support concurrent negotiation, the bidding phase of the CNP should reflect the fact that some of the pending offers can be accepted.

Let O be the set of tasks for which a production agent has sent offers and no award or regret message have been received. Since that it is very difficult to include in the production agent reasoning capabilities in order to make in determine to whom tasks will be awarded, the process of evaluating the bid will be an heuristic one.

The marginal cost of adding the announced task t to the current set of scheduled tasks T is now bounded below by $bid^{-}(t)$, determined as

$$\min_{P \subseteq O}(cost(best\_plan(T \cup P \cup \{t\})) - cost(best\_plan(T \cup P)))$$

and above by $bid^{+}(t)$, determined as

$$\max_{P \subseteq O}(cost(best\_plan(T \cup P \cup \{t\})) - cost(best\_plan(T \cup P)))$$

Note that $bid^{-}(t)$ is not necessarily equal to the marginal cost determined in equation 1, since that some of the tasks may be interdependent and the execution of more tasks may indeed reduce the total cost of the plan. In fact, that value could be used as an estimative for the marginal cost in this concurrent negotiation setting, but it implements a very radical behavior where an agent does not expect that any of its bids will be accepted. In order to solve this problem, each of the production agents is characterized by a parameter α, ranging from 0 to 1, that determines which of the values of the interval is chosen. The bid that is submitted for the execution of the task t is thus determined as

$$bid(t) = bid^{-}(t) + \alpha \times (bid^{+}(t) - bid^{-}(t))$$

The parameter α can be used to define the risk attitude of the production agents. In order to implement an optimistic agent, a value of α near 0 should be used, since that in this situations the agent assumes that the marginal cost of executing one more task is the lowest possible. On the contrary, a value near 1 defines a pessimistic agent that always expects an high increase in the total cost when adding another task to its local plan.

In the awarding phase the allocation agent simply chooses the lowest ,bid submitted, sends the award to winning production agent and regrets to the remaining agents of the production stage.

V. THE PRODUCTION AGENTS ARCHITECTURE

The production agents exhibit the most complex behavior of all the system agents. In order to accomplish its tasks more effectively by enhancing the execution parallelism, it was divided in four modules, each one implemented by a different process (Figure 3.):

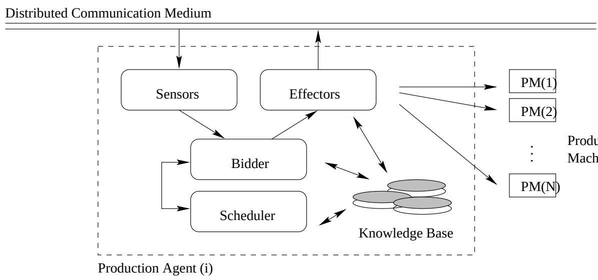

Figure 3. Production Agents Architecture.

- *Sensors.* This module is responsible for sensing the shared environment in order to detect the messages addressed to the agent.
- *Effectors.* Responsible for sending the messages to the other agents through the shared environment and for executing the plans by transferring the low-level orders, needed to execute the tasks, to the production machines associated with the agent.
- *Knowledge base.* Module that stores the list of low-level orders that are necessary to execute each task.
- *Bidder.* Responsible for the evaluation of the bids that the agent will submit to each announce. This evaluations are done according to the formulas presented in the previous section.
- *Scheduler.* It implements the local optimizer needed to determine the best execution plans. Since that our framework is independent of the type of optimizer used, it is not presented a detailed description of this module.

VI. CONCLUSIONS AND FUTURE WORK

The application of economic decision approaches to the previous simulation model brought the ability to control intelligently work allocation in each production stage, tunes global production tasks coordination and improves significantly intelligent agent cooperation. Thus, it is possible to define better production plans and optimize the overall system performance.

The possibility of using concurrent negotiation when determining the best production agents to execute the tasks, enlarges the applicability of this framework by enabling the simulation of more realistic production environments.

In the future we intend to extend this framework to multi-enterprise environments, where the allocation agents are allowed to submit bids to production agents of foreign enterprises. If the bids submitted by foreign production agents are lower than the ones from the local agents, the allocation agents outsource the execution of the tasks.

This improvement will further extend the applicability of this framework, since it will enable the modeling of enterprises where some of the production stages are completely outsourced (i.e., production stages without production agents) or even totally virtual enterprises.

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