Multi-Agent System for Dynamic Production Scheduling and Optimization

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Abstract. A major challenge for today's manufacturing organizations is how to respond agilely and cost-effectively to dynamic fluctuations of demand patterns across product mix and increasing rates of new products introduction. As traditional process planning and production scheduling operate independently for process plans and production schedules generation respectively, production schedules generation processes become inflexible and is restricted by the pre-generated process plan. In response to this issue, a multi-agent Monte Carlo configuration and optimization method is proposed to integrate process planning, production scheduling, and resource optimization for concurrent evaluation of planning and scheduling options. The principle of this methodology is to integrate agent bidding mechanism and Monte Carlo optimization, in which agents perform iterative interactions to evaluate production decisions dynamically for an optimum solution determination.

1 Introduction

In order to survive and preeminent in today's turbulent market environment, which is characterized by dynamic fluctuations of demand patterns across product mix and increasing rates of new products introduction, manufacturing organizations have the need to respond agilely to the turbulent market environment. Conventionally, process planning and production scheduling are accomplished independently in a sequential manner. A process plan is generated without the consideration of alternative scheduling options in a manufacturing shop floor and a production schedule is generated using the pre-generated process plan without considering alternative planning options. Since there is no co-operation between the planning and the scheduling functions, production schedule generation processes become inflexible and are restricted by the pre-generated process plan. In response to this issue, many researchers have proposed to integrate process planning and production scheduling for concurrent and dynamic evaluation of alternative planning and scheduling options. In this paper, a novel configuration and optimization methodology that focuses on simultaneous evaluation and optimization of production decisions using an agent-based approach, termed as Multi-Agent Monte Carlo Configuration and Optimization Approach (MACOA) is proposed. Agents are autonomous entities that operate co-operatively and allow simultaneous decision-making. As the number of alternative system configurations (i.e. integration of process plans for all manufactured products in a shop floor) to be evaluated is large, a heuristic optimization method using Monte

Carlo principle is used to cyclically optimize the generated system configurations with respect to a predefined objective function. The optimization cycle terminates when the value of the objective function reaches a saturated point.

The remaining structure of this paper is arranged as follow. Section 2 provides a literature overview of some agent related research in process planning and production scheduling. Section 3 presents the proposed configuration and optimization approach, MACOA. The MACOA architecture, agent bidding mechanism, and optimization algorithm are also illustrated. Section 4 provides the results obtained using MACOA based on a test case. Section 5 draws a conclusion.

2 Agent Related Research in Process Planning and Production Scheduling

In recent years, Multi-Agent System (MAS) [1] has been an active research topic in manufacturing arena [2]. Due to the difficulties in solving process planning and production scheduling problems using traditional centralized problem solving methodology, MAS approach – a distributed problem-solving paradigm is used as another attempt to solve the planning and scheduling problems. As a distributed problem-solving paradigm, MAS breaks complex problems into small and manageable sub-problems to be solved by individual agents co-operatively.

An agent-based dynamic scheduling and rescheduling approach for manufacturing systems [3] is proposed. This approach utilizes Machine Agents, which represent machines, Tool Agents, which represent tools and Worker Agents, which represent workers to select resources and generate production schedules simultaneously via a multi-agent bidding mechanism. Machine Agents, which receive tasks from a Machine Mediator will negotiate with Worker Agents via a Worker Mediator and Tool Agents via a Tool Mediator to generate a desired production schedule. The role of the mediator is to select the most appropriate alternative (e.g. machine) among the available/capable alternatives. As all agents update their data continuously, real time scheduling and rescheduling becomes relatively easier.

A novel algorithm termed as Distributed Probabilistic Scheduling (DPS) [4] is proposed for dynamic production scheduling. DPS defines a probabilistic time window in which Resource Holons can schedule tasks received from Order Holons dynamically. Probabilistic time window expresses the likelihood that an order will be processed by a particular resource throughout the scheduled time period. DPS provides the predicted load over time for each resource by considering the resources' current and past load information, which facilitates resource allocation decisions and dynamic scheduling.

Autonomous Agents for Rock Island Arsenal (AARIA) agent architecture that integrates customers, suppliers, and manufacturing shop floor for manufacturing shop floor control and scheduling is proposed [5]. Customer agents and supplier agents are created to represent customers and suppliers respectively. Part Persistent Agents, Resource Persistent Agents and Process Persistent Agents are created to represent information of parts, information of resources, and information of processes that remain unchanged over the time scale respectively. Part Transient Agents, Resource Transient Agents, Process Transient Agents, and Engagement Transient

Agents are created to represent parts, resources, processes, and agreements between agents, which changes throughout the production stage respectively. AARIA agents interact in a hierarchical manner, in which the higher-level agents impose constraints on lower-level agents, and the lower-level agents pass status information back to the higher-level agents.

A part dispatching approach that utilizes intelligent agents and Evolutionary Algorithm (EA) is proposed [6-7]. Th aim of this work is to determine a part dispatching decision which involve resource selection and process route selection in a dynamic manufacturing environment. Here, the part dispatching decisions are taken by Part Agents (PA), which represent manufactured items/parts and Machine Agents (MA), which represent machines in a manufacturing shop floor. Each PA identifies alternative machines that are capable of processing a part and selects the machine that has the highest performance with respect to a set of weighted criteria (i.e. processing time, setup time, etc.). On the other hand, each MA selects the next part to be processed from its input buffer. The MA always selects the part with the highest degree of satisfaction in all weighted criteria (i.e. processing time, due date, etc.). Initially, weights are assigned to each criterion based on the influence of the criterion in the computation of each system performance (i.e. makespan, resource utilization, throughput, etc.) obtained from simulation studies. Then, EA and a fuzzy multi-criteria algorithm are used to find the optimal weights (corresponding to all criteria) that allow agents to make the most appropriate dispatching decision that satisfies all system performances.

An agent-based manufacturing system scheduling and control approach that utilizes the concept of stigmergy [8] (i.e. a coordination mechanism found in insect society) is proposed. Here, Order Agents, Resources Agents, Pheromone Objects, and dissipation environments are created. Order agents and resource agents represent production orders and manufacturing resources respectively. They act as problem solvers, information observers, information creators, and information spreaders. Pheromone objects represent information corresponding to Order Agents/Resource Agents. Information distribution algorithm (i.e. upstream/downstream spread of information at the dissipated environments with a stopping criteria controlling the information distribution processes) and information gathering algorithm (i.e. continuous updating of information) are encoded within the pheromone objects. Dissipation environments represent locations i.e. conveyors, production facilities and crossings where order agents can take alternative process routes. A layered control algorithm is built within the dissipation environments to control the overall agents' performance. This layered control algorithm comprises feasibility layers, optimizing layers, and tuning layers. Feasibility layers ensure that the fundamental requirements/constraints such as avoiding deadlock, preventing routing parts through route that it cannot be finished on time, etc. is fulfilled so that production orders are able to meet production due dates. Optimizing layers ensure that the production objectives of a routing option such as maximizing throughput, avoiding bottleneck, etc. are fulfilled. Each routing option is assigned with a probability value indicating the probability that the option will be selected. Routing option selection is accomplished randomly using Back-Pressure Algorithm [9]. Tuning layers determine the parameter values used in the optimizing layers. In this approach, agents do not

interact directly with one another, but indirectly via information/pheromone dropped at the dissipated environments.

3 Multi-Agent Monte Carlo Configuration and Optimization Approach (MACOA)

MACOA is a system configuration and optimization approach that integrates multi-agent bidding mechanism and Monte Carlo optimization methodology. As the name manifests itself, MACOA is constructed by a cluster of autonomous agents. There are a Workshop Agent (WA), Machine Agents (MAs), Transport Agents (TAs), and Product Agents (PAs), which represent modelled manufacturing shop floor, machines, material handling devices, and manufactured products (one PA per product) respectively. The internal agent architecture can be found in [10]. All MACOA agents share a common global objective, i.e. to generate an optimum system configuration. Each agent also has a local objective i.e. to determine the most appropriate scheduling option with respect to a set of criteria.

In order to illustrate the functions of MACOA, the MACOA's scheduling and optimization scenario is presented. A manufacturing system producing various products is considered. Each product has various features to be processed. The production sequence of these features is indicated by a process sequence. In MACOA only one process sequence is considered per product. For each feature, there are alternative machines that are capable of processing the feature. When machines (with production schedules) are selected for all features corresponding to a product, a process plan is generated. A process plan is considered as a feasible process plan when the production due date of the product is not violated. Each product has a process plan and the integration of process plans (of all products) forms a system configuration. When different machines are chosen for a production feature (i.e. different machine combinations), alternative process plans are generated. The integration of alternative process plans give rises to alternative system configurations. As the number of machine increases, the number of alternative process plans increases. As the number of process plans increases, the number of alternative system configurations also increases. In order to determine a feasible and most cost-effective system configuration, the following questions need to be resolved. What is the most appropriate combination of machines (i.e. involve resource selection) that will form a feasible process plan of a product? What is the most appropriate combination of process plans (i.e. involve global objective optimization) that will form an optimum system configuration? Section 3.1 provides the answers to the above questions.

3.1 MACOA Mechanism

Fundamentally, the MACOA mechanism involves two stages. The first stage is the local decision-making stage, which involves an agent-bidding mechanism for simultaneous resource (i.e. Machine Agent, MA) selection and production schedule generation based on time-cost criteria at a particular discrete time interval. As the

global objective of MACOA agents is to manufacture products with low cost (i.e. cost) and to meet production due dates (i.e. time), time-cost criteria are considered here. In order to determine the optimum combination of time-cost criteria that will draw the most appropriate MA for a particular production feature, weights are assigned to each MA per feature per criterion. The performance μ_{ij} of a MA *i* that is processing a feature *j* is computed as in Equation 1.

$$\mu_{ij} = W_{i,j,T} * \frac{t_{min}}{t_j} + W_{i,j,C} * \frac{c_{min}}{c_j} \quad (1)$$

$W_{i,j,T}$ and $W_{i,j,C}$ are the weights for production time and production cost respectively. t_j and c_j are the production time and production cost respectively. t_{min} and c_{min} are the minimum production time and production cost among the MAs that are capable of processing feature *j* respectively. MA with the highest performance is preferred. The second stage is the global objective optimization stage, which involves iterative weights updating using Monte Carlo method for solution (i.e. system configuration) refinement with respect to the agents' global objective. Agents' interactions take place in both of the stages. Figure 1 depicts the schematic representation of MACOA mechanism. Section 3.1.1 and Section 3.1.2 illustrate the first and second stage of MACOA mechanism respectively.

3.1.1 The Local Decision-making Stage

1. Initially, one Product Agent (PA) will call for proposals from Machine Agents (MAs) that are capable (in terms of process capability) of processing the first production feature (new process) corresponding to a process sequence of a product.
2. MAs that have the processing capabilities of performing the new process will determine the most appropriate way of scheduling the new process via buffer manipulation. Alternative schedules corresponding to the new process are generated by inserting the new process before each existing job followed by right shifting of the affected existing jobs. Affected existing jobs refer to jobs with conflicting schedules. Each scheduling option is considered as a feasible option if the due dates of all other products are not violated and the production cost of the option does not exceed the production cost of placing the new process at the end of the buffer queue (i.e. the original scheduling option).
3. Prior to agent bidding processes (bid for the new process called by PA), MAs will calculate their performances using time-cost criteria as aforementioned. In order to compute the production time i.e. sum of setup, loading, operation, inspection, unloading, waiting, and transportation times and production cost i.e. sum of setup, loading, operation, inspection, unloading, waiting, and transportation costs, MAs will determine their transportation information. This is accomplished by examining the linkage relationships between themselves and their previous sources (i.e., previous MAs or storage that have the outputs transferred to the

MAs by transporters). Suppose various direct relationships (i.e. previous sources are linked to MAs by conveyor belts) are found, MAs will obtain the transportation times (that reside within their databases) corresponding to various sources and calculate their performances. Each MA chooses the source that allows it to have the highest performance. Conversely, when direct relationships do not exist, MAs will call for proposals from Transport Agents (TAs).

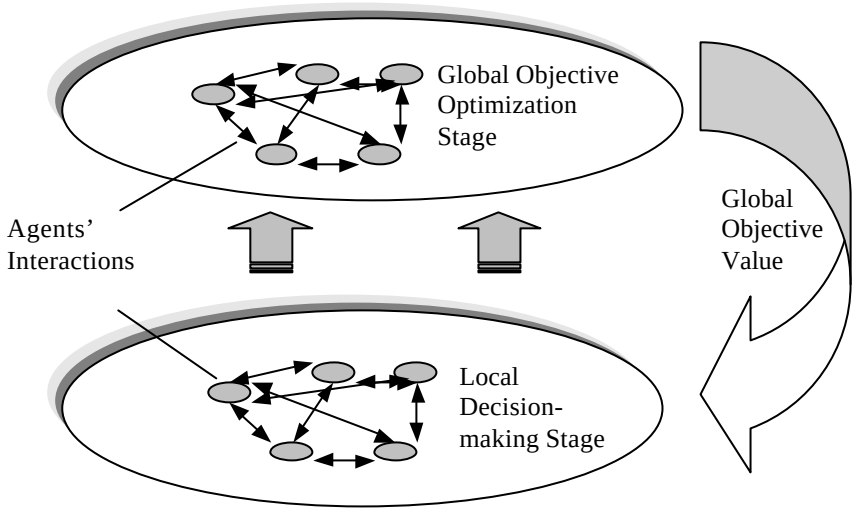


Fig. 1. MACOA Mechanism

4. TAs will calculate their transportation times required to perform the transportation tasks. Then, TAs will send their proposals containing transportation times and costs back to corresponding MAs.
5. Pursuant to the proposals obtained from various TAs, MAs will calculate their performances. Again, each MA will select the TA that allows it to have the highest performance and rejects other TAs.
6. MAs will send their proposals, which consists of their performances to PA for new process bidding.
7. PA will select a MA that has the highest performance, and offer the new process to the MA.
8. PA will call for proposals from MAs that are capable of performing the subsequent processes in the process sequence until all processes are assigned to a MA.
9. Other PAs will resume Steps 1-8 for other new products. A system configuration is generated when all processes corresponding to all new products are allocated.

3.1.2 Iterative Weights Updating using Monte Carlo Method for Solution Refinement With Respect to An Agents' Global Objective

In order to determine the desired combination of time-cost weights that will draw the most appropriate Machine Agents (MAs) to form an optimum system configuration, the time-cost weights are updated with respect to the agents' global objective in an iterative manner using the Monte Carlo optimization methodology (refer Figure 2).

1. At the beginning of the training process, the Workshop Agent (WA) will randomly generate initial weights. These weights will be encapsulated in a Current Weights Vector ($\overrightarrow{CW}$).
2. WA, PAs, MAs and TAs will interact with one another (Section 3.1.1) to generate a system configuration (Current System Configuration, CSC) using $\overrightarrow{CW}$. If the CSC is infeasible (due date of at least one of the product cannot be met), the $\overrightarrow{CW}$ will be discarded and a new $\overrightarrow{CW}$ will be generated until a feasible CSC is found.
3. WA will calculate the total manufacturing cost (Current Cost, CC) corresponding to the feasible CSC. Total manufacturing cost is the sum of production costs corresponding to all machines constituting a system configuration.
4. WA will generate another set of random weights and encapsulates these weights in a Random Weights Vector ($\overrightarrow{RW}$).
5. WA, PAs, MAs and TAs will interact with one another to generate another feasible system configuration (Random System Configuration, RSC) using $\overrightarrow{RW}$.
6. WA will calculate the total manufacturing cost (Random Cost, RC) corresponding to the feasible RSC.
7. WA will compute the third set of weights and encapsulate these weights in a Learnt Weights Vector ($\overrightarrow{LW}$). $\overrightarrow{LW}$ is computed as follow:

$$\overrightarrow{LW} = \frac{\frac{\overrightarrow{CW}}{CC}+\frac{\overrightarrow{RW}}{RC}}{\frac{1}{CC}+\frac{1}{RC}}$$

$$= \frac{(RC*\overrightarrow{CW})+(CC*\overrightarrow{RW})}{CC+RC} \qquad (2)$$

8. WA, PAs, MAs and TAs will interact with one another to generate another feasible system configuration (Learnt System Configuration, LSC) using $\overrightarrow{LW}$.
9. WA will calculate the total manufacturing cost (Learnt Cost, LC) corresponding to the feasible LSC.

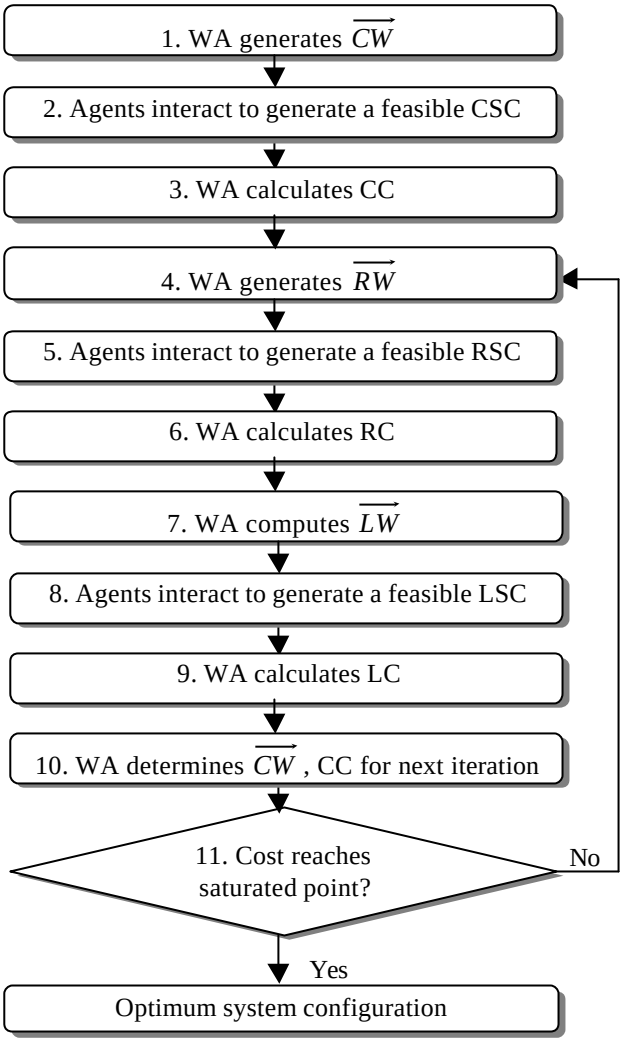


Fig. 2. MACOA Optimization Algorithm

10. WA will determine the $\overrightarrow{CW}$ and CC for the next iteration as follow:

$$\overrightarrow{CW} = \left\{ \begin{array}{ll} \overrightarrow{CW} & if \quad CC = min(CC,RC,LC) \\ \overrightarrow{RW} & if \quad RC = min(CC,RC,LC) \\ \overrightarrow{LW} & if \quad LC = min(CC,RC,LC) \end{array} \right\} \tag{3}$$

$$CC = min(CC,RC,LC) \tag{4}$$

11. The training processes will reiterate until total manufacturing cost reaches a number of periods of time. At that point, a near optimum system configuration is expected. This system configuration will be a feasible system configuration that yields near minimum total manufacturing cost.

4 Test Case

A manufacturing cell as depicted in Figure 3 is used as a test case to evaluate the feasibility of MACOA mechanism. The cell consists of eight machines (i.e. represented by eight MAs) and one transporter (represented by TA). It is assumed that all machines are reachable by TA. Only one process sequence is considered with alternative machines capable of processing each feature in the process sequence. The cell is currently processing three products. Two new products are to be scheduled within the cell.

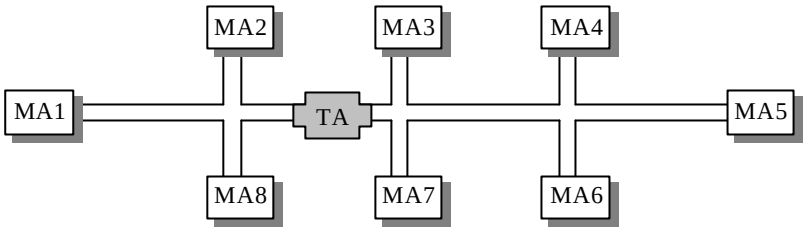


Fig. 3. A Manufacturing Cell

Here, four MA decision-making scenarios for resource selection and production schedule generation are considered and compared. There are MACOA methodology that based on time-cost criteria (Section 3.1), Shortest Processing Time (SPT) dispatching rule, Earliest Start Time (EST) dispatching rules, and minimum manufacturing cost selection rule. In the case of SPT and EST, both dispatching rules yield similar results, in which a feasible system configuration is generated i.e. all products are able to meet production due dates with a manufacturing cost of 3701.42. In the case of minimum manufacturing cost selection rule, in which agents select

resources and scheduling options based on lowest manufacturing cost, an infeasible system configuration is generated. In the case when MACOA methodology, a feasible system configuration with a minimum total manufacturing cost is generated. Figure 4 depicts the result obtained using MACOA method. Note that the total manufacturing costs decrease as the training iteration increases. The minimum manufacturing cost i.e. 3602.60 is found at iteration number 721.

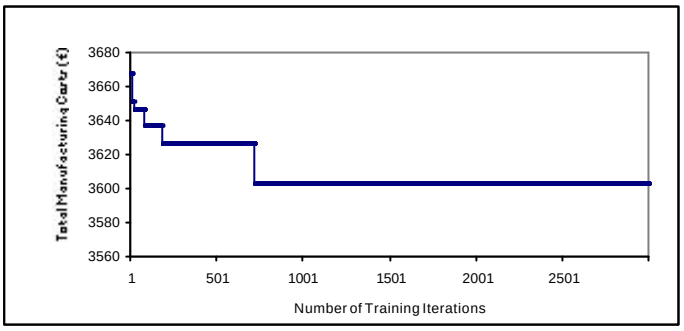


Fig. 4. Total Manufacturing Costs obtained using MACOA Approach

5 Conclusion

A manufacturing optimization and configuration approach that integrates multi-agent bidding mechanism and Monte Carlo optimization methodology is proposed. This methodology is proposed to help manufacturing organizations to cope with the dynamic fluctuations of demand patterns across product mix and increasing rates of new products introduction via concurrent and dynamic evaluation of production decisions with regard to resource selection and production scheduling. The main contributions of this paper are (1) the integration of multi-agent system with Monte Carlo optimization methodology for concurrent evaluation of production decisions, and (2) the segmentation of configuration and optimization problem into two stages that are dynamically interacting with one another until a solution is concluded.

However, further testing on MACOA methodology is needed on a more sophisticated test case to solidify this research work. Currently, MACOA methodology is evaluated on a test case that reviews different structures i.e. production cells, workstations, etc. of a manufacturing system. The idea is to test the feasibility of MACOA methodology when structural constraints i.e. limiting the productions of all features corresponding to a product within a specific manufacturing subsystem such as production cell, production line, etc. is imposed to a manufacturing shop floor.

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