Optimize Resource Utilization at Multi-site Facilities with Agent Technology

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Abstract. Many enterprises expanded their manufacturing environment from localised, single-site facility to more globalised, multi-site facilities. This paper proposes a multi-agent system, using its characteristics of autonomy and intelligence, to integrate process planning and production scheduling across different facilities, so as to secure the most efficient and cost-effective plan and schedule to meet the demand. A currency-based agent iterative bidding mechanism is developed to facilitate the coordination of agents. A genetic algorithm is employed to tune the currency values for agent bidding. In this paper, a case study is used for simulation in order to demonstrate the effectiveness and performance of the proposed agent system.

Keywords: Multi-agent system, multi-site manufacturing, genetic algorithm

1 Introduction

Due to rapid expansion of market, vigorous acquisition and new facility development have taken place among manufacturing enterprises. The manufacturing has evolved from localized, single-site facility to more globalised, multi-site facilities [1]. Process planning and production scheduling are two manufacturing functions traditionally treated as separate operations and majority of works predominantly focuses on single-site facility and the methodologies are not designed for multi-site optimization. In the literature, multi-site research specifically in integrated process planning and production scheduling is rather limited, and hence the focus of this paper. Furthermore, multi-agent system (MAS) is a popular and promising tool for solving complex problems, such as in multi-site research, but yet its application in this area, particularly related to integrated process planning and scheduling, is rare. Therefore, this paper will investigate the performance and effectiveness of employing MAS to optimize process planning and production scheduling within multi-site manufacturing environment.

This paper is organized as follows. Section 2 reviews the literature in process planning and production scheduling and the use of MAS in this domain. Section 3 defines the case study used and Section 4 describes the agent model and currency-based agent

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iterative bidding mechanism for multi-site resource optimization. Section 5 explains the genetic algorithm for currency tuning to facilitate agent bidding, and followed by simulation analysis in Section 6. Finally, a conclusion will be given in Section 7.

2 Literature Review

2.1 Process Planning and Production Scheduling

In order to have an efficient process planning and scheduling, it is necessary to have simultaneous assessment of process planning and scheduling decisions [1]. There are a number of approaches to integrated process planning and production scheduling that can be found in the literature. These approaches can be classified into non-linear process planning (NLPP), closed-loop process planning (CLPP), and distributed process planning (DTPP) [2]. NLPP generates possible alternative plans for each part prior to actual shop floor production. All the possible plans are ranked according to the process planning criteria. For an efficient planning and scheduling, it is vital to have feedback from the shop floor and CLPP provides such feedback by taking into account of the shop floor status at that time [3]. DTPP performs in parallel and in two phases. The first phase is pre-planning, i.e. process planner analyses the operations to be carried out based on product data. The second phase is final planning, whereby the operations will be matched against the capability of the available resources.

All these research works predominantly applied on single-site facility; very limited attention has been paid to optimizing process planning and production scheduling within multi-site manufacturing environment. Most research in multi-site has been focusing on more strategic issues, e.g. with regard to integrating production planning with distribution systems [4]. Chung et al. [5] applied a modified genetic algorithm for process planning and scheduling in multi-factory environment. The aforementioned works have limited focus on ways to optimize resource utilization within multi-sites, taking into account of the complexity of multi-site environment. To assist decisions making for multi-site optimization, MAS has been suggested by Wang and Chan [6] as a promising tool and their future research work.

2.2 Multi-Agent System (MAS)

The system consists of a group of intelligent autonomous agents interacting with each other to achieve a global goal, while bearing their own objectives to fulfill [7]. The agent's characteristics of intelligence and autonomous decision-making have attracted a large number of researchers using it to solve complex problems in manufacturing domains [8]. However, these works are mainly on research domains related to single-site manufacturing facility. There is a small number research works using agent concept in multi-site manufacturing facilities [9]. Based on the literature, most agent-based research focuses on strategic issues, e.g. improving communication/information sharing between multi-plants, but less on operational issues, such as integrating operational functions (e.g. process planning and production scheduling) to optimize the resources in multi-site facilities. This paper is aimed at addressing this gap.

3 Case Study

The make-to-order enterprise has two manufacturing facilities and recently acquired a new facility at a nearby location. All these facilities operate on cellular manufacturing systems whereby machines are grouped into cells based on the type of manufacturing processes offered. Each cell in each facility has different manufacturing attributes, such as machine capability (e.g. productivity, tolerance precision, quality, reliability) and availability, machine setup, production cost, shop floor layout, etc.

When a customer places an order, the challenge is how to take advantage of owning these facilities by sharing the available resources, so as to secure the most efficient and cost-effective process plan and production scheduling to fulfil the order. This process and scheduling plan should optimize the overall utilization of resources in multi-site environment at the lowest (transportation and production) cost possible. In this study, we predominantly consider operations between the multi-site manufacturing facilities (mainly on transportation) and within each facility (production-related) with certain constraints.

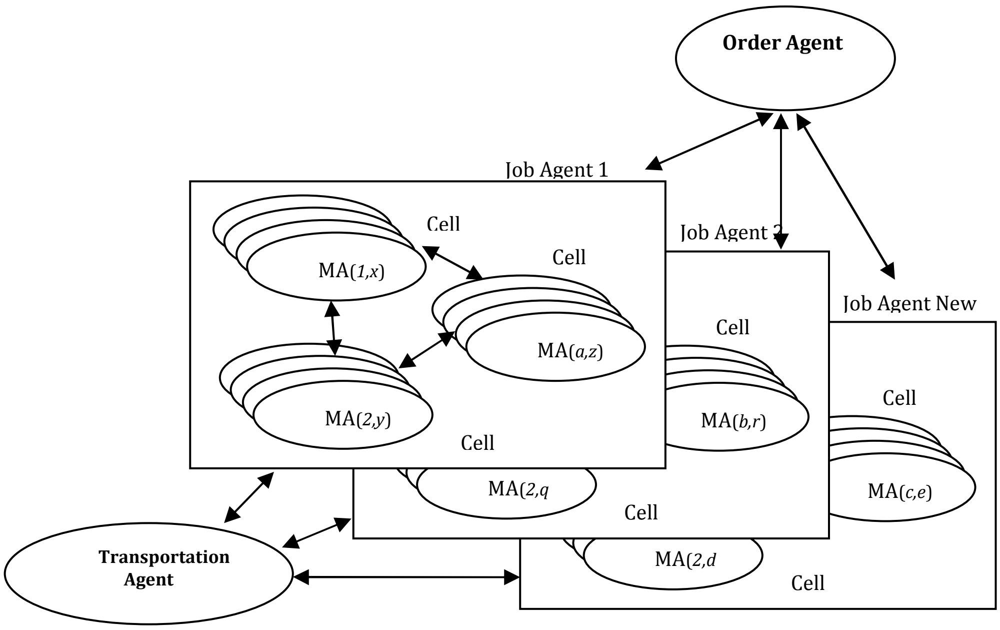
4 An Agent Model for Multi-Site Manufacturing Facilities

4.1 Agent Model

In this study, the key entities in the multi-site manufacturing environment are represented by agents (Fig. 1). There is an order agent representing an order placed by a customer. A job agent represents a job (i.e. a series of operations to produce a batch of components ordered) to be performed, the responsibility of which is to identify the most appropriate manufacturing resources to fulfill the order. Each facility will be assigned with one job agent. In each facility, each machine in the cells is represented by a machine agent. These machine agents will interact with each other in order to find a group of machines to produce the components from within the same facility. In order to explore the possibility of obtaining better machines, the agents will extend their search to look for alternative machines in other facilities. A transportation agent represents the available transportation between the facilities. When there is a need to transport WIP between these facilities, the transportation agent will provide the necessary information and determines if the service requested is available.

4.2 Currency-Based Iterative Agent-Bidding Mechanism

A currency-based iterative agent bidding mechanism is proposed to perform dynamic integration of process planning and production scheduling in multi-site environment. The bidding process begins when the order agent informs job agents of a new order, and the job agent announces the job to all machine agents in their respective facility to bid. The announcement includes the information in relation to the machining operations required for the job and the virtual currency value assigned to each operation. Machine agents that have the technical capability to perform the first operation will come forward to become 'leaders', whose responsibility is to search for other machines to perform the remaining operations. The leaders then announce the second operation to all machine agents within the same facility, including the leaders themselves. To offer better bids, the machine agents may reschedule and optimize their machine buffer by shifting jobs if other operations' due dates are not violated. This aims to produce optional (and hopefully, better) bids.



MA(x,y) = machine agent representing y^{th} machine in cell x

Fig. 1. Agent model

Machine agents construct their bids in production cost and lead time. Individual machine cost and lead time is a sum of various elements, defined from operational data.

$$C_i = C_{ti} + C_{wi} + C_{si} + C_{pi} + C_{ri} \tag{1}$$

where $$C_{ti} = C_{ti/d}(D)$$

$$C_{pi} = C_{pi/t}\left(\frac{V_{removed}}{MRR}\right)$$

where C_{ti} = transportation cost from the preceding machine (unit of cost) $C_{ti/d}$ = transportation cost / unit of distance (unit of cost), D = distance from the location of preceding machine (m), C_{wi} = holding cost (unit of cost), C_{si} = setup cost (unit of cost), $V_{removed}$ = volume to be removed in order to produce the feature (mm^3), *MRR* = material removal rate (mm^3 / unit of time), C_{pi} = processing cost (unit of cost), $C_{pi/t}$ = processing cost / unit of time (unit of cost), C_{ri} = rescheduling cost (unit of cost).

The individual lead time is populated as:

$$T_i = T_{ti} + T_{wi} + T_{si} + T_{pi} \tag{2}$$

Where

$$T_{ti} = T_{ti/d}(D)$$

$$T_{wi} = \sum_{j=1}^{n} t_{wi[j]}$$

Where T_{ti} = transportation lead time from preceding machine (unit of time), D = distance from the location of preceding machine (m), $T_{ti/d}$ = transportation lead time / unit of distance (unit of cost), T_{wi} = waiting time at buffer, i.e. queuing time/bottlenecks (unit of time), $\sum_{j=1}^{n} t_{wi[j]}$ = total waiting time of *n* jobs scheduled in the job buffer before the currently bidding job (unit of time), T_{si} = setup time (unit of time), T_{pi} = processing lead time (unit of time), $V_{removed}$ = volume to be removed in order to produce the feature (mm^3), *MRR*= material removal rate (mm^3 / unit of time).

As to whether to forward a bid for an operation, the machine agents will base on the amount of virtual profit earned which is above a set threshold value. By shifting jobs in the job buffer, a machine agent may put forward more than one bid as long as the virtual profits are above the set threshold. When the bids are received, the leader will select winning bid that provides the shortest lead time. This process is continued until whole set of operations to be performed is concluded. Job agent evaluates the resulting job plan for due date adherence which can be denoted as follow:

$$T = \sum_{i=1}^{n} T_i^{win}, \qquad C = \sum_{i=1}^{n} C_i^{win} \tag{3}$$

The job agent evaluates the bids with the aim of fulfilling the due date D and achieving minimum total production cost C:

$$Min\left(C=\sum_{i=1}^{n}C_i\right)$$
$$T=\sum_{i=1}^{n}T_i \le D \tag{4}$$

If the due date is not fulfilled (i.e. T > D), or the cost is not considered minimum, the virtual currency allocated to operations will be tuned in the next iteration to look for a better plan. If the due date cannot be fulfilled after a predefined iteration, the leader will search across different facilities to find optimal plan, which is then forwarded to order agent to decide.

Based on Eq. 3, the order agent will award the job to the outstanding machine group and this will be conveyed to the machine agents through the respective job agent. The machine agents in the group will then update their loading schedules.

5 Genetic Algorithm (GA) for Currency Values Tuning

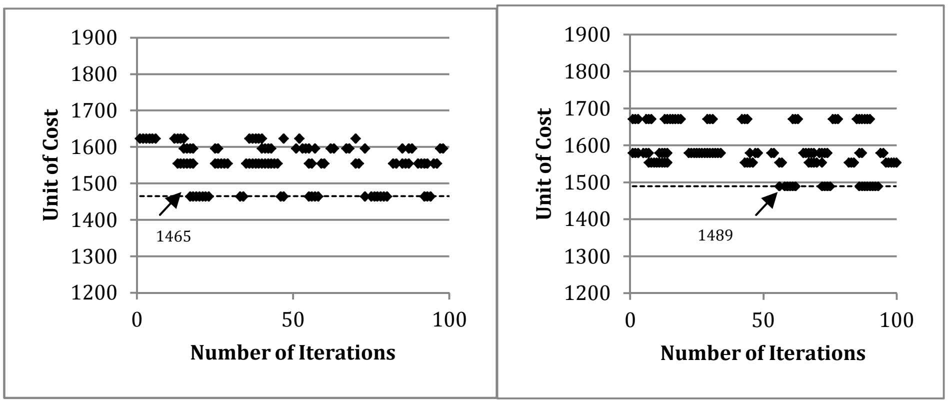
In this study, GA is used by the job agents to tune the currency values iteratively in order to search for better and better process plans and schedules. The following describes the GA process:

1. Gene coding: A population of chromosomes (POP_SIZE) and a generation number (GEN) are determined. The genes in each chromosome represent the currency values allocated to the features in a component.
2. Evaluation of fitness function (announcement to machine agents): The job agent evaluates the bids from the machine agents for the best solution at this iteration.
3. Selection of chromosomes (“select-all” strategy): All the chromosomes have equal opportunity to be selected for crossover and mutation operations.
4. Crossover process, then Mutation process
5. Re-announcement to machine agents: The offspring chromosomes in the new population (achieved through above steps) are announced to machine agents, and chromosome which the bid carries the least production cost and satisfies the product due date, is recorded as the best solution found at this iteration. Steps 3-5 are repeated till the Gen number is achieved.

6 Simulation and Discussions

The MAS proposed in this study was implemented on Java Platform. Two orders, with details about features to produce in sequence, were placed at interval times to produce a batch of parts each, namely PA and PB. The currency values were an estimate based on history data. The simulation of iterative mechanism commences with the order agent analyzing the process requirements, and followed by announcing the jobs of producing PA to all job agents and let them coordinate with the machine agents to find the best machines to perform the jobs. This process repeats for PB.

The best bid (which was considered to be near-optimum) for part PA received by the order agent has a production cost of 1465 units and lead time of 942 units put forward by the job agent of Facility B, Fig. 2. When the leader extended its search to other facility, no overall best bid was obtained.



(a) Within Facility B (b) Across all facilities

Fig. 2. Bids received for part PA by job agent at each GA iteration in Facility B.

The same GA parameters were used for the next order placed to produce a batch of 80 units of part PB. The overall best bid received to produce part PB has a production cost of 2308 units and lead time of 1448 (Fig. 3). It was found that the best bids received by the job agents were the same as presented in figures above, however the simulation time has increased approximately triple of the generation size of 100 iterations. The bids received at each iteration are spread out as previous runs shown above.

7 Conclusions

This paper proposed a multi-agent system (MAS) to optimize the resources within a multi-site manufacturing environment, in particular through the integration of process planning and production scheduling. Each agent has individual objectives and a global goal to achieve. The global goal of the MAS is to find an optimized process plan and schedule (within a facility and across different facilities) that gives the lowest production cost while satisfying all requirements such as due date and product quality, while the machine agent's objective is to win the operation jobs and optimize its machine utilization, and the job agent is responsible for assigning the operations to the outstanding group of machines. The simulation results show that as the currency being tuned at each iteration and so does the bidding process, different bids were constructed. This is aimed at increasing the opportunity to explore wider non-elite solution spaces, so as to finding better and better bids optimizing resource utilization.

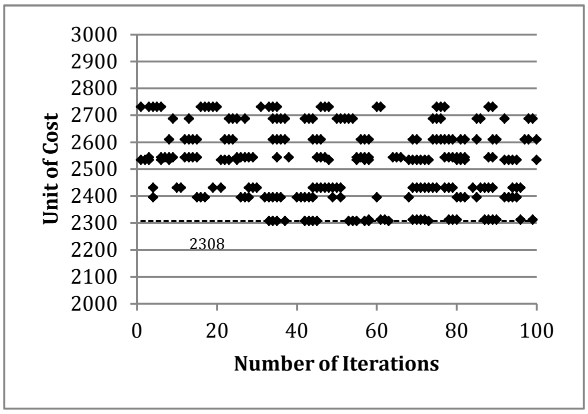


Fig. 3. Bids received for part PB by job agent at each GA iteration in the new facility (for across all the three facilities).

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