# A RULE-BASED SCHEDULING SYSTEM FOR AUTOMATED MACHINING

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## ABSTRACT

An automated machining system involves concurrent use of manufacturing resources, alternative process plans, and flexible routings. High investment in the installation of automated facilities requires an efficient scheduling system that is able to allocate the resources specified for operations over a scheduling horizon. The primary emphasis of this paper is to generate schedules that accurately reflect details of the automated environment and the objectives stated for the system.

In this paper, a scheduling algorithm for automated machining is presented. Using the previous simulation research for this topic, a rule-based scheduling system is constructed. An architecture for an intelligent scheduling system is proposed, and the system has a high potential to provide efficient schedules based on the task-specific knowledge for the dynamic scheduling environment

## I. INTRODUCTION

Automated machining systems may involve sophisticated information systems to control automated equipment. The equipment typically includes (Groover 1987):

- Automated machine tools to process parts
- Automated assembly machines
- Industrial robots
- Automated material handling and storage systems
- Computer hardware for planning, data collection, and decision making to support manufacturing activities

The benefits offered by automated manufacturing systems are as follows (Cowan 1985) :

- Fast response to market demands
- Better product quality
- Reduced cost
- Better resource utilization
- Reduced work in process
- Flexibility

With the development of automation technology, its supporting systems - planning, scheduling, and control - have gained importance. Production planning involves establishing production levels for a known length of time. It determines production parameters, such as product mix, production levels, resource availability, and due dates. With the specified production parameters, the goal of scheduling is to make efficient use of resources to complete tasks in a timely manner (Newman and Kempf 1985). There have been extensive studies on scheduling manufacturing systems. These studies can be divided into three basic approaches :

- Operations Research (OR) approach
- Artificial Intelligence (AI) -based approach

- Combination of OR and AI-based approaches

The literature on scheduling manufacturing systems using operations research techniques is rather extensive. Panwalkar and Iskander (1977) divided these studies into the following two categories:

- Theoretical research dealing with optimization procedures
- Experimental research dealing with dispatching rules

Cohen and Feigenbaum (1982) categorized expert systems in manufacturing as hierarchical, non-hierarchical, script-based (skeleton), opportunistic, and constraint-directed expert systems. The most common characteristics in expert systems category are as follows (Shaw and Whinston 1986):

- on-line decision support,
- schedule operations dynamically,
- coordinate manufacturing resources,
- synchronize processes for different jobs, and
- monitor the execution of plans.

Several surveys of expert systems for manufacturing applications have been published in the literature (Steffen 1986, Jaumard et al. 1988, Kusiak and Chen 1988, Marucheck 1989). The operations research-based approach usually focuses on finding the "best" schedule under the deterministic constraints, while a number of artificial intelligence approaches focus on finding of a "feasible" schedule subject to probabilistic constraints. As pointed out in Phelps (1986), there are some of similarities between the two approaches:

- face similar problems,
- use models for problem solving,
- use heuristics when optimal methods are not suitable, use mathematics,
- use computers for their implementations, and
- employ interdisciplinary analysts and designers.

O'Keefe et al. (1986) presented a view that expert systems and operations research methods are complementary instances of a broad range of decision making tools. Kanet and Adelsberger (1987) suggested that the expert scheduling systems of the future will have the reformulative ability (by expert system techniques) along with the best available algorithmic scheduling knowledge (by operations research techniques). Jaumard et al. (1988) identified operations research tools can be useful in intelligent problem solving.

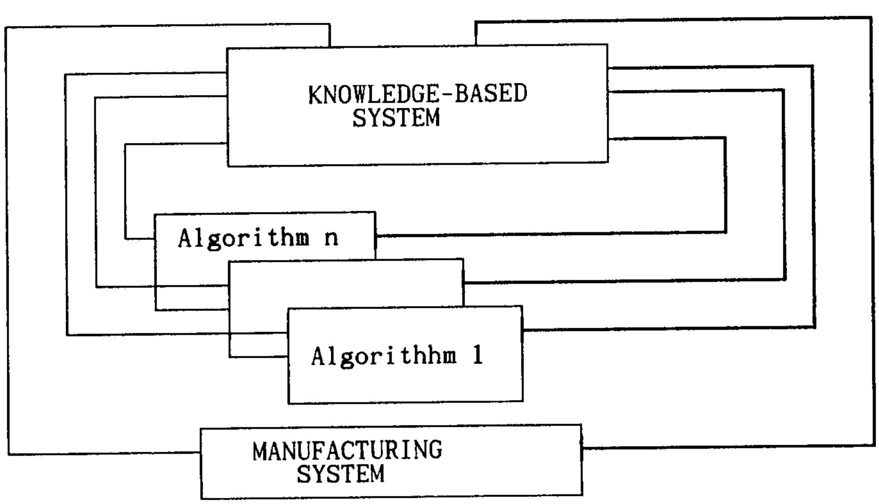


Figure 1. Multi-model tandem arc itecture(thin arrows:data flow: thick arrows:solution flows)

Perhaps the most promising architecture that is able to incorporate operations research and artificial intelligence techniques in scheduling manufacturing systems is the tandem architecture (see Figure 1) suggested by Kusiak (1987). The tandem system has been designed so that a knowledge-based system interacts with algorithms. The algorithm deals mainly with quantitative and deterministic component of the scheduling problem, guaranteeing rigorous generation of schedules. At the same time, the knowledge-based system deals mainly with qualitative and probabilistic elements of the scheduling problem. Incorporation of the two approaches is possible through the communication channel. In the subsequent sections, a rule-based scheduling system implemented in the tandem architecture is described. A tandem expert system architecture considered in this paper has the following characteristics (Kusiak and Chen 1988) :

- Capability of solving difficult problems
- Flexibility for solving problems of various types
- Modularized development and implementation
- Sharing of intellectual resources with other control and management systems
- Increased role of communication between subsystems

## II. THE SCHEDULING FRAMEWORK

Scheduling an automated machining system involves concurrent use of manufacturing resources, alternative process plans, and flexible routings. Kusiak and Ahn (1990) developed a dispatching rule (MDR rule) which has been designed to maximize the utilization of resources in a resource-constrained machining system. Ahn and Kusiak (1990) analyzed the performance of a number of dispatching rules for various scheduling scenarios. The analysis was done under the assumption that the required data are complete and certain. Likewise, the objectives were assumed to be specified in advance. In many practical applications, however, scheduling under the assumption that data are complete is not practical due to unpredictable and changing manufacturing conditions. For the schedules to be flexible so that they could be updated and modified in response to the changes in the scheduling environment, algorithms should be integrated with a rule-based system.

### II-1. Scheduling Algorithm

The scheduling algorithm has been implemented so that static as well as dynamic part arrivals are handled. Before the algorithm will be presented, the following notation and definitions are introduced:

$f_{ik}$ : completion time of operation k

$r_{ik}$ : remaining processing time of operation k

$s_k$ : status of operation k ;

$$s_k = \begin{cases} 1, & \text{if operation k is schedulable ,} \\ 2, & \text{if operation k is nonschedulable ,} \\ 3, & \text{if operation k is being processed ,} \\ 4, & \text{if operation k has been completed ,} \\ 5, & \text{if operation k satifies the first two conditions in the definition of schedulability} \end{cases}$$

$sr_{cr}$ : status of resource r of type c ;

$$sr_{cr} = \begin{cases} 1, & \text{if resource cr is avaliable ,} \\ 0, & \text{otherwise} \end{cases}$$

$S_j$ : set of operations with $s_k = j,\ j = 1,\dots,5$

$C_j$ : temporal set of operations

Scheduling Algorithm

Step 0. Initialize the variables.

- Set current time $t = 0$
- Set resource status, $sr_{cr} = 1$, for all r and c
- Operation status and sets of operations with the operation status are initialized as follows :

(i) Set $S_1=S_2=S_3=S_4=\emptyset$

(ii) For each part, if operation k has no predecessor operations then $s_k = 1$; otherwise, $s_k = 2$

(iii) Construct $S_1$ and $S_2$ for operations in (ii)

Step 1. If all the operations have been completed, STOP; otherwise go to Step 2.

Step 2. If $S_1 = \emptyset$, go to Step 5; otherwise, go to Step 3.

Step 3. Select an operation k*q# in the set $S_1$, based on a dispatching rule provided ( part i* corresponding to operation k*q# is automatically selected ).

Step 4. Set :

- Remaining processing time of operation k*, $rt_{k*} = t_{ik*q\#}$
- Resource status $sr_{cr} = 0$ for $cr \in R_{k*q\#}$

Construct :

- $C_1 = \{q \mid q \in A_{i*k*} \setminus q^{\#}\}$
- $C_2 = \{kq \mid kq^* \neq q^\#,\ [k^*_{q\#}, k_q] \in Q_{i^*},\ k_q \in S_1\}$
- $C_3 = \{kq \mid \{k^*_{q\#},\ k_q\} \in N_{cr}$ for all c and r, $k_q \in S_1\}$

Update :

- Set of schedulable operations $S_1 = S_1 - \{k^*_{q\#}\} - \{C_1 \cup C_2 \cup C_3\}$
- Set of nonschedulable operations $S_2 = S_2 \cup C_2 \cup C_3$
- Set of processing operations $S_3 = S_3 \cup \{k^*_{q\#}\}$

If $S_1 \neq \emptyset$ , go to Step 3 ; otherwise, go to Step 5.

Step 5. Set :

- Completion time $f_k = rt_k + t$, $k \in S_3$
- Current time $t = t + 1$
- Remaining time $rt_k = rt_k - 1$

If $rt_{k*}=0$ in $k \in S_3$, then resource status $sr_{cr} = 1$ for $cr \in R_{k*q\#}$

Step 6. In set $S_2$, construct :

- $C_1 = \{k_q \mid$ all the preceding operations of operation $k_q$ have been completed $\}$
- $C_2 = \{k_q \mid sr_{cr} = 1,\ c^r \in R_{kq}\}$
- $C_3 = \{k_q \mid$ current time - completion time of the immediate preceding operation of operation $k_q$ $> \tau$[immediately preceding operation of operation $k_q$ , $k_q$]$\}$

Update :

- Set of schedulable operations $S_1 = S_1 \cap \{C_1 \cap C_2 \cap C_3\}$
- Set of nonschedulable operations $S_2 = S_2 - \{C_1 \cap C_2 \cap C_3\}$
- Set of processing operations $S_3 = S_3 - \{k^\#\}$
- Set of completed operations $S_4 = S_4 \cup \{k^\#\}$

Step 7. Go to Step 1.

## II-2. Rule-Based Scheduling System

In the algorithm presented in the preceding section, once a dispatching rule is selected, all parts are scheduled regardless of manufacturing conditions. In some cases, the schedules may be infeasible due to unpredictable and changing manufacturing conditions (eg., blocking or machine breakdowns). Moreover, it is evident that the "blind" selection of a dispatching rule might result in an inefficient schedule.

In this paper, the manufacturing conditions are divided into the following categories:

1. Exogenous manufacturing conditions
   - scheduling objectives (eg., maximization of resource utilization, minimization of the number of tardy parts, and so on.)
   - system load levels
   - resource constrainedness (the ratio of the number of constrained-resources to the number of unconstrained-resources)
   - due date assignment (eg., constant, slack-based, total work-based, and so on)
   - due date tightness
2. Endogenous manufacturing conditions
   - changing shop status (eg., inventory status, queuing status, bottle-neck resource status, machine breakdown, and so on)
   - preference constraints (priority of temporal scheduling objectives)

Based on the two categories of manufacturing conditions, appropriate dispatching rules and scheduling algorithms are selected (exogenous manufacturing condition), and/or modified (endogenous) by a rule-based scheduling system. The need to construct such a system arises from the fact that :

1. An automated manufacturing system requires a dynamic and accurate scheduling.
2. There is no evidence in the literature that there exists a dispatching rule that performs best under all manufacturing conditions.
3. The existing scheduling studies present the performance of dispatching rules only for narrow domains.
4. The computational results indicate that combining the MDR and other dispatching rules may depend on the manufacturing conditions.

A rule-based system developed in this paper consists of four components : algorithm selector, rule selector, process reactor, and rule base.

<u>Algorithm Selector</u>

Algorithm selector determines a scheduling algorithm to be used in solving a problem considered. It comprises of a set of production rules or, alternatively, a user may specify the name of the model desired. One of the main advantages of the tandem archtecture is that it handles multiple models. In this paper, only one algorithm is introduced while there are many other scheduling algorithms available in the literature (see for an example Kusiak 1990).

<u>Rule Selector</u>

Rule selector provides a global dispatching rule for the scheduling algorithm, based on the exogenous manufacturing conditions. A global dispatching rule selected is fired whenever a dispatching decision is made (see Step 3 of the algorithm), unless there is a significant change in the machining shop status during the scheduling horizon. Once an inadmissible change is detected on the shop floor, the process reactor is activated to minimize the schedule disruption. The process reactor fires a temporary dispatching rule. If the equilibrium on the shop floor is restored, then the global rule begins dispatching operations.

<u>Process reactor</u>

Process reactor communicates on-line with the manufacturing facility in order to respond to the endogenous shop conditions. It modifies the processof selection of dispatching rules in the "warning" state, and imposes selection of operations in the "urgent" state. A warning state is issued when the system is likely to generate infeasible schedules, for example, the number of waiting parts in front of a machine exceeds 75% of its capacity. In the warning state, the process reactor consults with the rule base, and it assigns a temporary dispatching rule that may help attaining a normal condition. The selected temporary dispatching rule is used by the rule selector. An urgent state is issued when the schedule obtained is infeasible or it might become infeasible in the next scheduling time horizon due to, for example, blocking or preventive machine maintenance. If the above immediate situation calls for action extraneous to the dispatching rule, then the process reactor takes exception to the rule (see Step 4 and 6 of the algorithm). This is also possible through the communication with the rule base.

Rule Base

Rule base plays an important role in the entire scheduling processes. All the production rules in the rule base are divided into the following classes :

Class 1. Selects an appropriate algorithm to solve the problem (model selector).

Class 2. Selects an appropriate dispatching rule to solve the problem (rule selector).

Class 3. Modifies the selected dispatching rule to solve the problem (process reactor).

Class 4. Selects an appropriate operation to solve the problem (process reactor).

Several sample production rules are presented next.

**Class 1**

RULE1_1. IF the machining system has more than three machines
AND the number of operations in all the parts being scheduled exceeds 20
AND the scheduling problem considered has alternative process plans
AND traveling times are imposed
THEN solve it using the scheduling algorithm (presented in this paper)

**Class 2**

RULE2_1. IF the machining system has more than three machines
AND the number of operations in all the parts being scheduled exceed 20
AND the scheduling problem considered is static
AND the scheduling objective is to minimize the makespan
AND the resource constrainedness is high (RC > RC2)
THEN use the MDR/MSWR dispatching rule.

RULE2_2. IF the scheduling problem is dynamic
AND the scheduling objective is to minimize the number of tardy parts
AND the resource constrainedness is medium (RC1 < RC < RC2)
AND due dates are assigned with MWR method
AND the system is light-loaded
THEN use the MDR/COVERT 1 dispatching rule.

RULE2_3. IF the scheduling problem is dynamic
AND parts are produced for safety stock
AND the resource constrainedness is meduim (RC1 < RC < RC2)
AND the system is heavy-loaded
THEN use the LWR dispatching rule.

**Class 3**

RULE3_1. IF the machining system has more than three machines
AND the number of operations in all the parts being scheduled exceeds 20

AND the scheduling problem considered is static
AND the Work-in-process, W > W0
AND the LWR dispatching rule is not used
THEN replace the current dispatching rule with the LWR rule.

**Class 4**

RULE4_1. IF the number of parts waiting in front of a bottleneck machine
THEN override the current dispatching rule
AND find a feasible schedule.

RULE4_2. IF a machine is down
THEN set the machine status to unavailable during that interval.

### Ⅲ-3. Knowledge Acquisition

An intelligent system should have learning ability. A system that learns is able to improve its own problem solving ability. In this section, a discrete simulation assisted knowledge acquisition process is described. The simulation is used for knowledge acquisition due to the following (Thesen and Lei 1986, O'Keefe 1986) :

- No domain experts are available.
- It is possible to build models that can predict the effects of input parameters on output measures.
- Practical rules of thumb and experience are needed to use simulation as an effective tool.

Computer simulation is a problem solving process of predicting the future state of a real system by studying an idealized computer model of the real system.

Table 1. Dispatching rules generating the best and the second best solutions in the static machining system for various performance measures

| performance | RC / Solutions | High | Medium | Low |
|---|---|---|---|---|
| AW | Best solution | LWR | LWR | LWR |
| | Second best solution | MDR+LWR | MDR+LWR | MDR+LWR |
| AF | Best solution | MDR+SPT | MDR+SPT | SPT |
| | Second best solution | SPT | SPT | MDR+SFT |
| AM | Best solution | MDR+MSWR | MDR+MSOR | MSOR |
| | Second best solution | MSWR | MDR+MSWR | MDR+MSOR |
| PT | Best solution | MDR+COVERT2 | MDR+MSR | MSR |
| | Second best solution | MDR+COVERT1 | MSR | MDR+MSR |
| MT | Best solution | MSR | MSR | MDR+MSR |
| | Second best solution | MDR+MSR | MDR+MSR | MSR |
| AT | Best solution | MDR+MSR | MSR | MDR+MSR |
| | Second best solution | MSR | MDR+MSR | MSR |
| CAT | Best solution | MDR+MSR | MDR+MSR | MSR |
| | Second best solution | MSR | MSR | MDR+MSR |

Simulation experiments are usually performed to obtain predictive information that would be costly or impractical to obtain with real devices (Widman and Loparo 1989). In our simulation, two normalized performance measures for parts and five measures for schedules (runs) are considered :

- Normalized Average Waiting (AW) time
- Normalized Average Flow (AF) time
- Normalized Average Makespan (AM)
- Normalized Average Percent Tardiness (PT)
- Normalized Average Maximum Tardiness (MT)
- Normalized Average Tardiness (AT)
- Normalized Conditional Average Tardiness (CAT)

Tables 1 illustrate partial knowledge obtained by simulation. For the details of simulation and output analysis, see Kusiak and Ahn (1990).

## III. SUMMARY

In this paper, an intelligent system for scheduling automated machining was presented. By incorporating operations research and artificial intelligence techniques (tandem architecture), the proposed system has a high potential to provide efficient schedules reflecting details of the automated machining environment and accomplishing the objectives of the system.

The current implementation of the system is being improved. More elaborate knowledge acquisition methods are being sought. Other scheduling algorithms can be easily incorporated into the existing system.

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