Proceedings of the 1989 Winter Simulation Conference
E.A. MacNair, K.J. Musselman, P. Heidelberger (eds.)

INTELLIGENT BACK END OF A GOAL DIRECTED SIMULATION ENVIRONMENT FOR DISCRETE-PART MANUFACTURING

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ABSTRACT

This paper discusses the issues involved in developing an intelligent back end for a goal directed simulation environment. The intelligent back end serves to analyze the simulation output and suggest changes to the model parameters that may lead the simulation towards the goals. The main thrust is on incorporating domain behavioral knowledge to the back end. A discussion on issues that need to be considered when conducting a simulation analysis of manufacturing systems is given. This is followed by a classification of manufacturing systems developed to aid in the development of the rule base. This rule base essentially emulates the thought process of a simulation analyst. Finally a sample rule base is given, followed by future research directions.

1. INTRODUCTION

Research in intelligent simulation environments is motivated by two major factors. The first is the dearth of simulation experts who can conduct a complete simulation analysis. Secondly, it is realized that a great deal of "intelligence" that is used for modeling and analysis is discarded once the project is completed. If a system has the capability to retain the knowledge used for, and gained by, the analysis of a particular system, that could be made available to another user analyzing a similar system. These two reasons are pushing researchers to build intelligent simulation systems that can make simulation a tool accessible to unskilled users.

Developments in the field of artificial intelligence, database systems, and the related hardware, has presented researchers with the opportunity to explore the possibility of building efficient knowledge based simulation environments. Efforts are underway to identify ways in which simulation and expert systems can be combined to obtain an effective analysis tool.

In a goal directed simulation environment, the modeler declares the knowledge about the system and defines the desired goals. The simulation system constructs the model, runs the experiment, compares the output with the desired goals, makes changes to the model parameters if necessary, and continues until the goals are reached or judged insatiable. Some work has been done in this area. Shannon (1988) gives a good overview of using knowledge based simulation in the analysis of manufacturing systems. Wadhwa *et. al.* (1987) describe one such system used in the design of flexible assembly systems. Their system, converts the user input obtained through an interactive dialogue, into a SLAM simulation model. Once the simulation is run, an intelligent back end suggests changes to the model parameters if the desired goals are not achieved. The system is implemented using OPS5. Ford and Schroer (1987) describe a system developed in Prolog. This system uses a natural language interface to extract information from the user and build SIMAN models. Their domain is restricted to electronic assembly systems. Seliger *et. al.* (1987) describe a system called MOSYS that uses both mathematical and simulation techniques, along with knowledge based modeling and analysis support. The mathematical models serve to generate rough-cut estimates of performance measures, while simulation is used for a more detailed study. Their system includes knowledge about experimental techniques and also knowledge about the domain - flexible manufacturing systems.

In all these reports, very little is mentioned about the kind of information that goes into the back end of an intelligent simulation system. Knowledge about the domain behavior is an important factor that determines the performance of a goal directed simulation system. This knowledge serves to replace the process expert, and gives advice on the changes that have to be made to the model parameters to achieve the desired goals. While the knowledge is available, it must be made explicit. This information has to be garnered and formalized before an effective rule base can be developed. It is this information that drives a goal seeking system towards the goal.

Very little has been reported on efforts to study the steps a simulation analyst takes to draw inferences from a simulation output. The objective of the research described in this paper is to identify and formalize the knowledge that helps the simulationist make intelligent decisions. The domain of the study is restricted to discrete-part manufacturing.

The next section discusses the general aspects of manufacturing systems and the issues involved in simulating such systems. This is followed by a section that discusses specific issues related to developing the rule base, a section describing a sample rule base and finally the conclusion.

2. SIMULATION OF MANUFACTURING SYSTEMS

Simulation analysis of manufacturing systems has come of age. However, complexities of modern day manufacturing systems make the exercise non-trivial. The common manufacturing issues that simulation is used to address are : (1) the need for and quantity of equipment and personnel, (2) performance evaluation, and (3) evaluation of operational procedures (Law, 1986). All three issues come into play at both the aggregate level and at the operational control level, the only difference being the level of detail is higher in the latter. A large amount of literature dealing with analysis of manufacturing systems discusses simulation of manufacturing systems. Only a few are described here to exemplify the range of problems of concern. In all these studies, it should be recognized however, that simulation is not used as an optimization tool. Rather it is a method by which alternatives can be compared and the better one chosen.

2.1 NATURE OF SIMULATION STUDIES

Modern manufacturing facilities are characterized by computer controlled equipment, automated material handling/transportation devices, job variety and complex job flow patterns. One example for this is the integrated circuit (IC) chip manufacturing facility. Such a facility is characterized by different job types moving in lots, with a flow similar to job shops, and frequent changes in product mix. Burman *et. al.* (1986) discuss the different approaches used to tackle such complex problems, and identify simulation as the most suited method for a complete analysis.

Another major problem confronting engineers in modern manufacturing facilities is the movement of material handling equipment. The advent of automated guided vehicle (AGV) systems, has brought along with its advantages, a host of control problems managers could have done without. Mayer and Talavage (1977) have studied a computer integrated manufacturing facility to identify the best storage space location and vehicle dispatching rule. Identification of the best vehicle dispatching rule, the determination of the best route, deadlock avoidance, and storage space location are some of the primary concerns of analysts.

The problems associated with modern manufacturing facilities also include the concerns of traditional manufacturing systems. These include capacity requirement analysis, buffer size determination, product mix, and job dispatching rules among others. Reasor et. *al.* (1977) deal with capacity analysis and resource management in a job shop, while Jeyachandra and Sargent (1978) discuss manpower allocation policies to improve product quality in a facility.

The above list is not exhaustive, but serves to highlight the variety of problems and systems that are being analyzed using simulation.

2.2 INFERENCE FROM SIMULATION OUTPUTS

The two major considerations in analyzing a manufacturing system are the system configuration and the operational behavior, the latter being dependent on the former. The interactions are best explained using an example :

Consider a simulation analyst studying a flow line with infinite inter-stage storage space. Let there be only one job type that flows through the system, all the jobs following the same sequence. Let the objective of the simulation be to determine a suitable service rate and the number of machines required at each stage of the flow line, to assure that the average time spent in the system by a job does not exceed a specified value, with a given level of significance. Once the sufficient number of runs has been made and the averages obtained, the analyst goes about analyzing the output. If the analyst finds the time-in-system to be higher than the specified value, he/she goes about trying to identify the reasons for this. In this particular case, a high time in system could be caused by one or more of the following reasons :

1. A very slow machine at some stage
2. A very unreliable machine at some stage
3. Inappropriate job dispatching rule
4. Job arrival rate too high.

A very slow machine is indicated by a high average queue size at that stage, and a very high machine utilization. A high queue build up with low machine utilization could indicate an unreliable machine. In that case, the analyst looks at the percentage of time a machine is idle due to breakdown. Queue build up could be rapid if the arrival rate is disproportionately high when compared to the service rate. Queuing theory says that the ratio of arrival rate to the service rate should less than for stability and that the system becomes unstable if the ratio approaches 1. The analyst also makes use of knowledge about dispatching rules in identifying the reason for high time-in-system.

It is apparent that the analyst examines certain indicators to diagnose the reason for high time-in-system. Depending on the indicators, availability of alternate choices, and other economic considerations, he/she arrives at a solution to overcome the problem. In this case, there are four ways in which the time-in-system can be reduced :

1. Increase service rate at slow machine
2. Add another machine at the stage with high queue build up
3. Change dispatching rule, if existing one is inappropriate
4. Decrease arrival rate

Each one of these have a certain effect on the time-in-system, and it is left to the analyst to decide on which will suit the conditions.

The same analyst, when analyzing a similar system, but with finite inter-stage storage space, has one more factor to contend with. Since there is a limitation on the number of jobs that can be held in the buffer, once the buffer becomes full, the previous stage becomes blocked. The only remedy for this is to provide alternate storage space. In the absence of this, the analyst tries ways to reduce the percentage of time a machine is blocked. The reasons for a machine to be blocked are :

1. The buffer space is not sufficient.
2. Service rate of the machine could be disproportionately higher than the next machine.

To reduce blocking, the analyst could do one of the following :

1. Increase storage space
2. Increase service rate at next stage
3. Increase number of machine at next stage
4. Reduce service rate at current stage

The analyst would want to consider these possibilities in addition to those considered earlier.

Now, in the same system, if there are two job types flowing, then the question of product mix comes into the picture. The arrival rate of one job will have an effect on the time spent in the system by both the job types. Moreover, dispatching rules between job types also come into play. So the analyst has two more factors to consider in addition to all the others mentioned earlier.

It is quite clear that depending on the system being analyzed, the analyst looks at certain indicators for guidance. Based on these, and the knowledge about the domain behavior, he/she takes the necessary action. There is a distinct relationship between the objective, system configuration, indicators, and the decision taken. To get a better understanding of this complex interrelationship, a classification scheme is developed based on the above factors.

3. CLASSIFICATION

The preliminary classification scheme is based on expert knowledge of manufacturing systems, and analysis of about 50 simulation studies reported in literature, and is given in Appendix A. The classification is based on factors that affect the analyst's approach to making inferences about the system behavior.

At the highest level is the system being analyzed. The analyst is basically concerned about the objectives of the simulation and the system characteristics. In conducting a simulation study, there are usually multiple objectives that have to be met. However, some objectives dominate over others. As an example, the objective will be to obtain a certain minimum throughput, and at the same time maximize the utilization of an expensive machine. In most cases, the throughput objective will be more important than the machine utilization objective. The objectives are therefore classified as primary and secondary. The system characteristics can be further classified into system parameters, physical characteristics, and material flow characteristics. System parameters refer to the model parameters such as arrival rate, service rates, etc., which may or may not be variable. To a large extent, the values of these parameters determine the output of the simulation. The system parameters are however, dependent on the objectives of the simulation, and the physical and material characteristics of the system.

Any manufacturing system has the following three elements : (1) resources like machines, tools, operators, etc., (2) jobs that flow through the system, and (3) buffer space for in-process inventory to smoothen the effect of the inherent randomness in system behavior. In addition to these, the system may or may not have special material handling equipment.

The classification is made in such a way that each element in the classification introduces an element of complexity that the analyst has to take into account when analyzing the system behavior. The elements of concern as far as the resources are concerned are reliability, process capability, whether the particular resource is available continuously or it is available at specified periods of time, whether the resource is dedicated to a single station or shared by different stations at the same time, and whether additional resources are required. An example for a shared resource is an operator who supervises two stations.

The manner in which the jobs are transported has an effect on the system performance measures. Machines could have dedicated transporters, or jobs could be transported in conveyors. Modern manufacturing systems have transporters like AGVS to transport jobs between stations. The use of transporters introduces additional factors such as transporter capacity and number, transporter reliability, deadlock avoidance, and transporter speed, that the analyst has to take into account.

The most important aspect of a manufacturing system that determines the complexity of analysis is the material flow characteristics in the system. The first issue is the number of job types that are processed in the system. Then the nature of job flow determines the complexity of analysis. Analysis is simpler if all jobs follow the same sequence, than if each job follows a random sequence as in a job shop. Moreover, jobs may come in batches, and move either one by one or in batches. For each one of these and other flow characteristics, the analyst takes a unique approach in making inferences about the system behavior.

The above classification serves as an aid in systematically analyzing the decision making process of the analyst, and formalizing the knowledge in the form of a rule base. This classification scheme can also be used by the intelligent front end, as a basis of extracting information about the system from the user. Since the building of an expert system is an evolutionary process, as more and more systems are analyzed, the classification scheme suggested may undergo some alteration.

4. DEVELOPMENT OF RULE BASE : A SAMPLE

Development of a rule base for a flow shop with infinite inter-stage storage space and no transporter is discussed in this section. By a flow shop, we mean a shop where all jobs follow the same sequence of operations. Jobs may not return to a previous machines. The three main objectives that will be considered in this discussion are reducing time spent in the system by the job, reducing work-in-process, and increasing throughput. In all these systems the machines may be unreliable. In conducting a simulation study, the analyst looks for the system configuration that yields him the required throughput or time-in-system etc.

The rule base is developed based on expert knowledge of system behavior. This knowledge is obtained from the literature and simulation studies made of similar systems. The knowledge pertinent to this example is given below.

Expert Knowledge 1

Lower work-in-process usually leads to lower time-in-system.

Expert Knowledge 2

Shortest processing dispatching rule reduces waiting time and hence time-in-system.

Expert Knowledge 3

Throughput cannot be higher than the job arrival rate. At best it can equal the job arrival rate. It cannot be higher than what can flow through the facility bottleneck.

Expert Knowledge 4

High time-in-system or work-in-process could be caused by any one of the following factors :

1. A very slow machine
   --> indicated by high queue build up and a high machine utilization.
2. A very unreliable machine
   --> indicated by high queue build up in front of the station and a low machine machine utilization, or a high percentage of idle time due to machine breakdown.

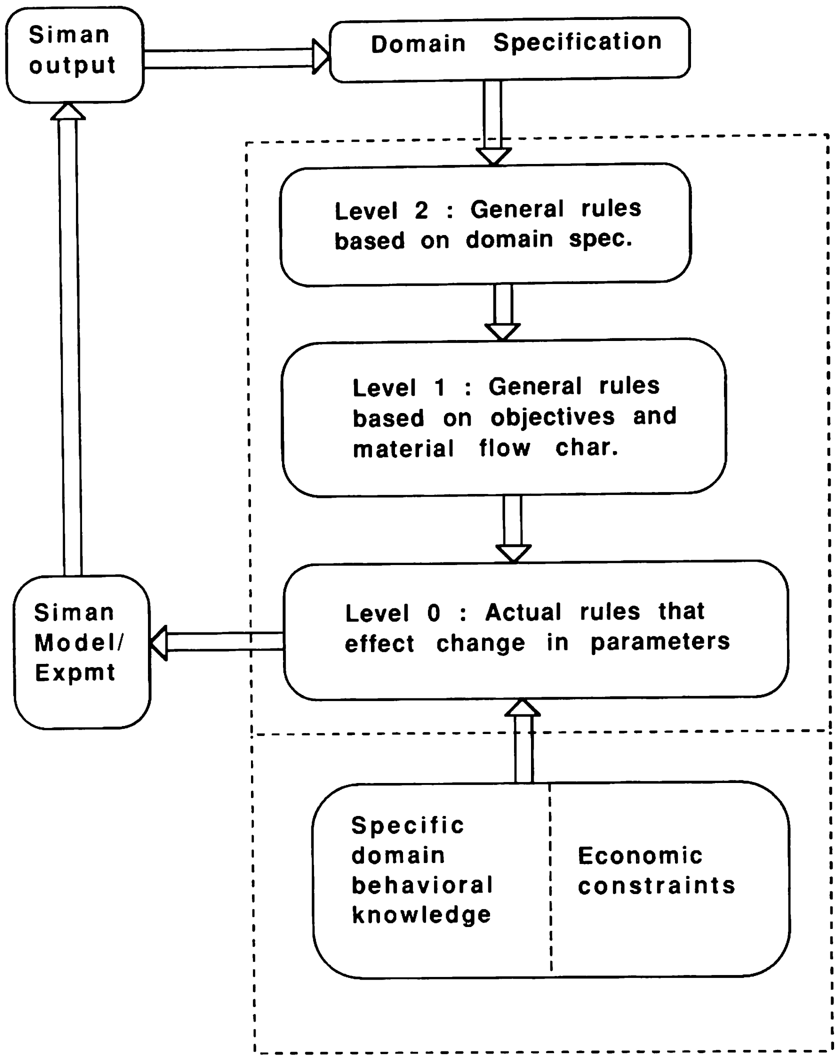


Figure 1 : Rule Base for the Goal Directed Simulation Environment

3. Arrival rate much higher than service rates
   --> queuing theory states that the system becomes unstable if the ration of arrival rate to service rate is close to one. For stability, arrival rate should be less than the service rate.
4. Unsuitable dispatching rule at any one of the stations
   --> indicated by high queue build up.

Expert Knowledge 5

Time-in-system can be decreased by increasing service rates at each station. This can be achieved by either increasing the service rate at each machine in the stations, or the number of machines in each station.

Expert Knowledge 6

Time-in-system can be decreased by reducing machine down time. This can be achieved by improving machine reliability, reducing time to repair, or by increasing the number of machines.

Expert Knowledge 7

Job waiting time can be reduced by reducing the arrival rates.

Expert Knowledge 8

All actions that reduce the time-in-system, except the reduction in arrival rates, also decrease the time between job release.

Expert Knowledge 9

Time-between-release can be reduced by increasing arrival rate.

It is apparent that the best indicators in identifying system bottlenecks for this system, are average queue sizes and machine utilization. Based on the above expert knowledge rules are developed for this system (Appendix B).

The general structure of the rule base is given in figure 1. At the lowest level (Level 0), the rules effect changes in the model parameters. The next level (Level 1) is a set of more general rules that make use of basic rules. These rules define the cause and effect relationships for different material flow patterns, and physical characteristics of the manufacturing system. It is at this level that the actual inference about the simulation output is made. The highest level (Level 2) serves to relate the system being analyzed to the classification scheme developed. This level determines the Level 1 rule that may be applied to a particular system.

In addition to these three levels, there is one more level that contains rules that are specific to the system being considered. This may include information on the dynamic behavior of the system, limitations of the system, economic considerations, any other information that may influence the decision. This information is important in deciding the specific course of action when confronted with alternate courses of action.

5. CONCLUSION

The paper discussed the issues involved in developing an intelligent back end for a goal directed simulation environment. A classification scheme based on physical characteristics, material flow patterns, and simulation objectives was developed to aid in the construction of the rule base. Finally, an example was given to describe the structure of the rule base.

The performance of a goal seeking system largely depends on how efficiently the search for the solution proceeds. Domain specific knowledge plays a key role in determining which parameters need to be perturbed, and by how much. Currently, work is going on at Texas A&M to identify this information that has to incorporated in the rule base to drive a goal seeking system towards the goal. The domain under consideration is IC manufacturing. The results of this will be given in a subsequent paper.

APPENDIX A: CLASSIFICATION

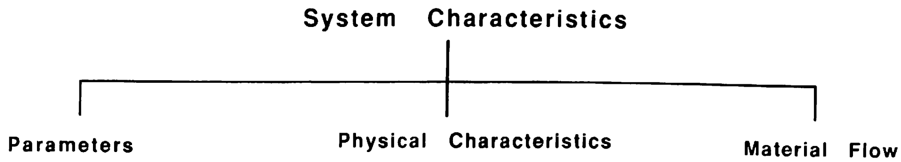
System

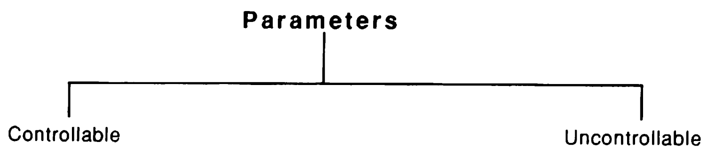
Objectives | **System Characteristics**

Objectives

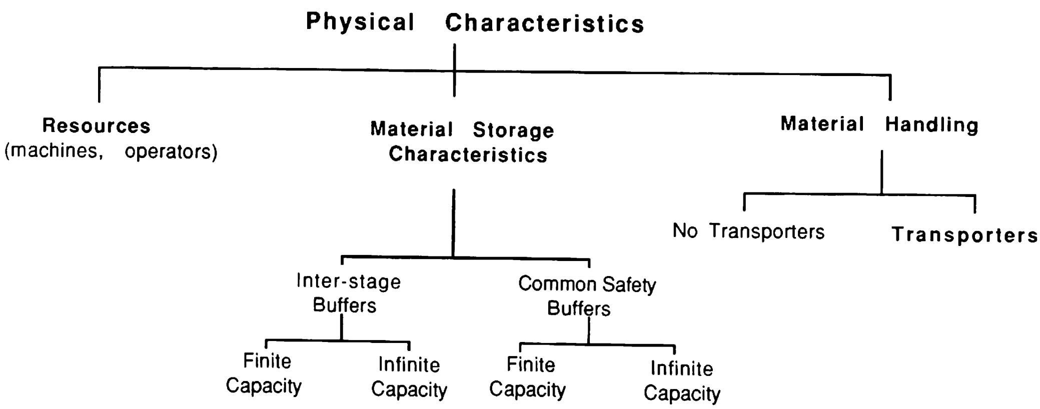
Primary | Secondary

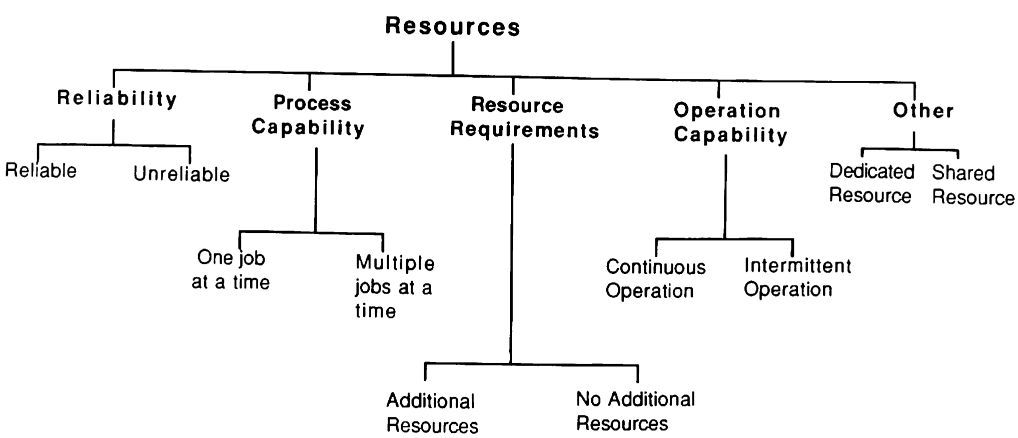
1. Time in system
2. Time between release (throughput)
3. Work in progress
4. Tardiness
5. Lateness
6. Resource utilization

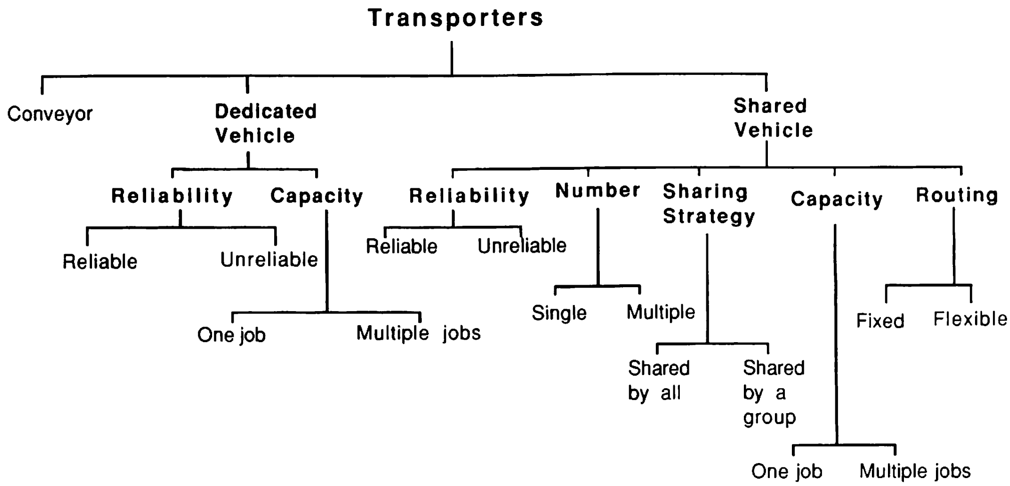


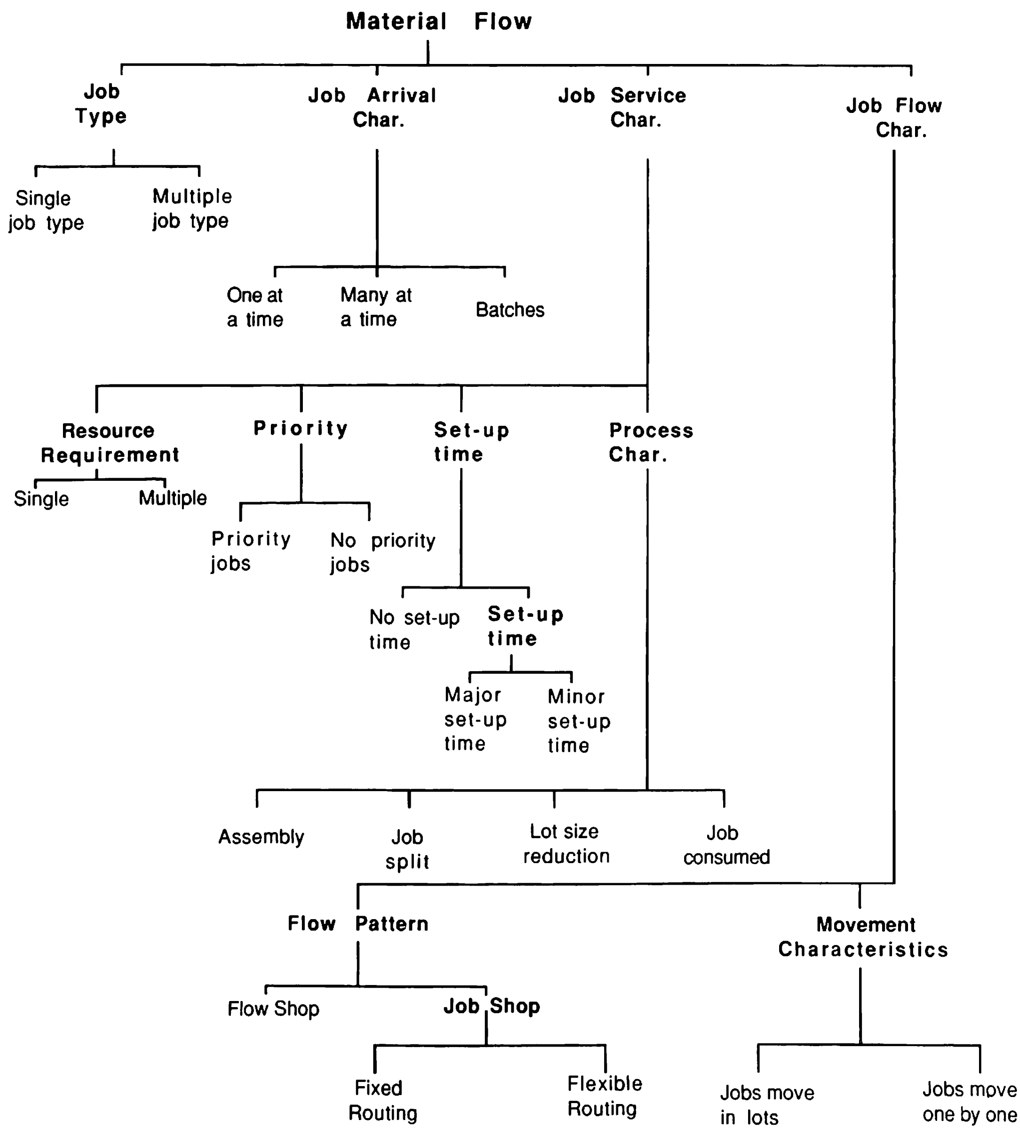


1. Job arrival rates
2. Service rates
3. Buffer sizes
4. Job dispatching rules
5. Number of resources
6. Resource capabilities
7. Transporter dispatching rules
8. Product mix
9. Inventory policies
10. Due dates






Transporters
Conveyor
Dedicated Vehicle
Shared Vehicle
Reliability
Capacity
Reliable
Unreliable
One job
Multiple jobs
Reliability
Number
Sharing Strategy
Capacity
Routing
Reliable
Unreliable
Single
Multiple
Shared by all
Shared by a group
One job
Multiple jobs
Fixed
Flexible


Material Flow
Job Type
Job Arrival Char.
Job Service Char.
Job Flow Char.
Single job type
Multiple job type
One at a time
Many at a time
Batches
Resource Requirement
Priority
Set-up time
Process Char.
Single
Multiple
Priority jobs
No priority jobs
No set-up time
Set-up time
Major set-up time
Minor set-up time
Assembly
Job split
Lot size reduction
Job consumed
Flow Pattern
Movement Characteristics
Flow Shop
Job Shop
Fixed Routing
Flexible Routing
Jobs move in lots
Jobs move one by one

APPENDIX B: SAMPLE RULES

Level 2 Rule :

```
if
  < single job type > and
     < flow shop with infinite interstage
          buffer > and
     < no transporter >
then
     begin
        < apply Rule1 >
     end
end if
```

Level 1 Rules :

Rule1

```
if
     < time-in-system .GT. goal time-in-system >
then
     begin
        if
          < machine utilization for all machines
                  .GT. 80% >
        then
          < apply SubRule4>
        else
          < identify station with maximum average
               queue size >
           < go to Loop 1 >
         end if
     end
end if

if
     < time-between-release .GT. goal
          time-between-release >
then
     begin
        < apply SubRule5 >
     else
        < identify station with maximum average
             queue size >
        < go to Loop 1 >
      end
end if

Loop 1 :  < compare machine utilization at that
               station with other stations >
          if
               < machine utilization is high >
          then
               begin
                    < apply SubRule3 >
               else
                    < apply SubRule2 >
               else
                    < apply SubRule1 >
               end
          else if
                < machine utilization is low >
          then
                begin
                    < machine is unreliable >
                    < apply Rule2 >
                else
                    < identify station with next
                         highest queue size >
                    < go to Loop 1 >
                end
          end if
```

Rule2

```
     if
          < machine is unreliable >
          begin
               < apply SubRule6 >
          else
               < apply SubRule7 >
          else
               < apply SubRule2 >
          end
     end if
```

Level 0 Rules :

```
SubRule1       if
                    < job dispatching rule not
                         proper>
               then
                    < use alternate dispatching
                         rule >

SubRule2       if
                    < number of machines at the stage
                         .LT. maximum number allowed >
               then
                    < increase number of machines
                         by one >

SubRule3       if
                    < service rate at machine .LT.
                         maximum allowable
                         service rate >
               then
                    < increase service rate >

SubRule4       if
                    < job arrival rate .GT.
                         minimum allowable
                         arrival rate >
               then
                    < reduce arrival rate >

SubRule5       if
                    < job arrival rate .LT.
                         maximum allowable
                         arrival rate >
               then
                    < increase arrival rate >

SubRule6       if
                    < machine repair time .GT.
                         minimum possible
                         repair time >
               then
                    < reduce repair time >

SubRule7       if
                    < more reliable machine is
                         available >
               then
                    < replace old machine >
```

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