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Resource Allocation, Batching and Dispatching in a Stochastic Flexible Job Shop

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Abstract. The problem of resource allocation and scheduling is considered for a flexible job shop composed of several work centers with multiple identical machines. Each machine has its own setup time that depends on the current and the arriving batch types. The optimal number of machines at each center and the optimal batch size for each job type is to be determined under various jobs dispatching rule. Several measures of scheduling performance are considered including the average flow time, sum of earliness and tardiness, and the number of tardy jobs. The simulation package ProModel is used to build the model and its optimization tool " SimRunner" is used for optimization.

1. Introduction

Resource allocation, batching and scheduling are three different optimization problems handled usually independently although in reality they are integrated with each other. Scheduling theory for example assumes certain resources allocated for performing certain tasks defined by job or batches. Solution of the integrated problem is usually difficult to handle especially under complex shop environment like the flexible job shop. The problem becomes more difficult under the existence of uncertainty. Sequence dependent setup times are usually additional source of complexity for scheduling problems. In reality all of these elements exist in job shop scheduling and planning environment, but it is rarely studied as a whole due to its complexity. Researchers usually study one of the three problems (resource allocation, batching, and dispatching rules) fixing the other two. For example, most of scheduling theories assume a fixed number of machines at each work center in the job shop and a fixed batching policy, where as in production planning literature, the optimum number of machine allocated in each work center, is studied for a given dispatching and batching policies. The problem is usually further simplified, either by assuming availability of data or ignoring sequence dependent set up times.

In this paper we study a dynamic stochastic flexible job shop problem. The requirement is to optimize resources by batching, scheduling (dispatching), and machine allocations in the work centers. Recently a comprehensive literature review focusing on problems involving scheduling and lot sizing with sequence-dependent setup times was given by Zhu and Wilhelm [1]. Their review covered all broad categories of scheduling problem along with various solution techniques including simulation. They listed only three articles on stochastic scheduling including the article by Kim and Bobrowski [2], on the job shop configuration.

Researchers have used artificial intelligence techniques to develop models such as expert systems, analytical hierarchical systems, among others to handle complex structures and multi-decision problems. Kusiak [3,4] used expert systems to decide which mathematical model and which resolution algorithm to use according to the available data and the problem size. Renato *et al* [5] used mathematical modeling to solve the capacitated resource selection problem where the objective is to minimize the sum of penalty costs and resource costs. Felix *et al* [6] developed an integrated approach for the automatic design of Flexible Manufacturing Systems (FMS). They analyzed the output from the FMS simulation models using the multi-criteria decision-making technique, the Analytic Hierarchy Process (AHP). Subramaniam *et al* [7] addressed the flexibility of job-routes in a manufacturing system. They carried out a simulation based study to propose three rules of machine selection in a dynamic job shop. Qu *et al* [8] used simulation to solve the problem of setting initial tooling and the operator requirements of a pilot production line. They also estimated the fixed and recurring costs for this production line.

Chtourou *et al* [9] developed a simulation based expert system for the selection of machines in a manufacturing system. The role of the expert system was to suggest the modifications in resources based on due date related performance measures. Cao *et al* [10] developed a combinatorial optimization model to simultaneously select the machines and their schedule while minimizing the costs of holding and tardiness. They found an optimal or near optimal solution to this problem through a Tabu search heuristic. Chen *et al* [11] developed a scheduling algorithm for the job shop scheduling problem with parallel machines and reentrant process. This algorithm uses two modules that help dispatchers in selecting one of the parallel machines and then to schedule the sequences and the timing of all operations assigned to each machine.

In the remaining of this paper, the problem will be formally defined and its complexity is demonstrated using a simple deterministic example. The simulation model is then introduced with its parameters and assumptions. Results are then introduced and discussed.

2. Problem Definition

We consider the problem in which jobs of different types are processed in batches of certain sizes in a flexible job shop consisting of several work centers. Each work center contains a number of identical machines working in parallel. Jobs arrive randomly and accumulate overtime to its predetermined batch size. Job processing times are not known in advance and may follow a certain distribution function. Changing production from one type of batches to another may require a time for set up which is dependent on the ordering of the two types. All machines in all centers are assumed to be continuously ready for processing. A constant travel time is assumed for the time taken by any batch to move between work centers. We assume that intermediate storage (buffer) is of infinite size and setup operations can be done only when the machine is completely free. Jobs are grouped into batches of *n* jobs of the same type. The batch is ready for processing when the batch is formed. A due date D_j is assigned for batch *j* as given by (1) below.

$$D_j = RT_j + U^*(TWK_j)^*n_j \qquad (1)$$

RT_j is the ready time of the batch j, *U* is a utilization factor and TWK is the total work content of the batch. TWK is calculated as the sum of the processing times on each machine visited and the travel time between the machines. The utilization factor reflects the tightness of the due dates. As the utilization factor increases a larger due date is assigned. Obtaining a value for the utilization factor generally done through the historical data and for this study a presumed value is assumed.

The requirement is to optimize resources by batching, scheduling (dispatching), and machine allocations in the work centers. Different performance criteria are considered for testing the performance of different possible dispatching decisions. We consider three performance measures namely minimizing the average sum of earliness and tardiness, mean flow time and minimizing the number of tardy jobs. Mean flow time reflects the utilization of the system, earliness reflects the inventory level and tardiness reflects customer satisfaction. The optimal configuration of the resources and the optimal batch size under different dispatching rules is determined with respect to each performance criteria.

In the following, a deterministic example is used to demonstrate the complexity of the manufacturing process and more importantly to validate the simulation model.

Example: Deterministic Case

Consider a job shop with five work centers and three types of jobs that arrive at the shop at different times with different machine routes. Jobs of type P1 are processed in the order (M3-M1-M2), jobs of type P2 are in the order (M2-M3-M4) and jobs of type P3 are processed in the order of (M1-M3-M5). Processing times as well as set up times for processing a job following any of the three job types is given in Table 1.

Machine Center	Parts Visiting	Proc. Time (min)	Setup Time (min)
M1	P1	5	(0, 10, 11)
	P3	5	(12, 13, 0)
M2	P1	3	(0, 14, 15)
	P2	3	(16, 0, 17)
M3	P1	12	(0, 18, 19)
	P2	10	(20, 0, 21)
M4	P2	7	(22, 0, 23)
	P3	10	(24, 25, 0)
	P3	5	(26, 27, 0)

Table 1. Data for the example

The batch size of each job type is taken as 10 and two batches of each type arrive at the shop. The targeted utilization factor U of 0.75. Assume also a travel time between the machines as 10 minutes. The due dates are now calculated as per function (1). Assuming that the ready time of batch 1 is 90 and batch 2 is 190, then the due date for each batch is calculated. Figure 1 shows the Gantt chart when First-in-First-Out (FIFO) dispatching rule is used.

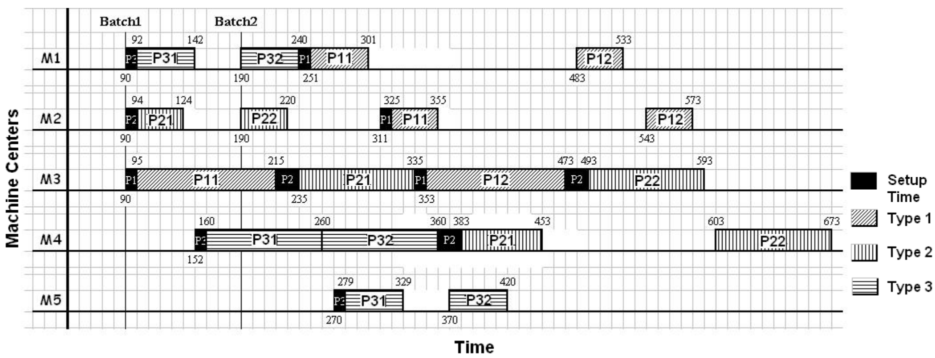

Figure 1. Gantt chart for the example

The evaluation of this schedule depends on the intended objective (performance measure). The generalization of this example is considered under stochastic job arrivals and stochastic set up times. The example is further generalized by having batch sizes and processing capacity (number of machines at each workstation) as decision variables. Simulation is used for analyzing the performance of different dispatching rules for different performance measures under this generalized problem.

3. Simulation Model

Due to the high stochasticness of the system and its high complexity in terms of shop structure and multiple decision levels, simulation based solution method is used. The model can be extended to any job shop structure or any form of stochasticness. Simulation can easily entertain the dynamic and stochastic aspects of certain factors in manufacturing and can provide a robust solution. The simulation package "ProModel" is used to build the model and its optimization tool "SimRunner" is used for optimization. The data for this study is obtained from Chtourou *et al* [9] for the resource selection problem and necessary input has been included for the modifications of the model, like sequence dependent setup times.

In this study we develop a simulation model for a specific shop structure consisting of 5 work centers and 3 types of jobs. This model can be easily extended to other similar shop structures. The model is built to study the performance of the shop under different scheduling (dispatching) decisions and data sets for different objectives. The data required for the simulation model is, distribution of inter-arrival times for different types of job, routes of each job type, processing times of jobs on different machines, setup times for each job type on all machines, and travel time for the jobs between work centers.

The preliminary results were analyzed using throughput as a measure and FIFO for dispatching to determining the warm-up period and the run length. Throughput is defined as number of batches produced in the system per hour. Figure 2 gives the graph for the throughput vs. run hours. The steady state starts where the curve stabilizes and thus the warm-up period can be taken as 400 hours. Further 800 hours are taken as the run length, making the simulation time 1200 hours. Considering the longer run length and the model stability after the warm up period, 10 replications were considered to be substantial to obtain reliable results.

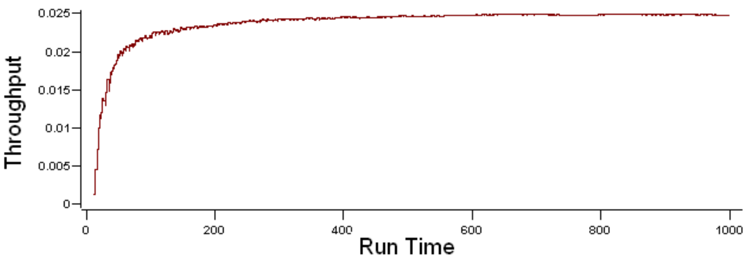

Figure 2. Steady state analysis

The optimization process starts with initializing the input parameters and identifying the performance measures for the simulation model developed in ProModel. A dispatching rule is then selected before a SimRunner project is developed based on the simulation model. The optimization decision variables are defined as macros and the SimRunner optimization process is run until it converges. The model tests multiple combinations of a range of variables to determine the best association of values. The number of machines for a work center is limited by 10 machines and the batch size is limited by 10 units. The model is run for different dispatching rules for the earlier mentioned performance measures and for each measure, the objective is to obtain the best combination of resources and batch size along with the suitable dispatching rule.

The suggested optimization process is applied for the problem setting similar to the one used by Chtourou [1] and is summarized in Table 2. The routing column gives the route for product type P1, P2 and P3 in the job shop. For example jobs of type P1 starts on machine 3, proceeds to machine 1 and then to machine 2. It takes 20 minutes for any batch to move between any two work centers. The TWK of job type 1 can be calculated as of sum of the processing times on the machines it has to visit. For example the TWK for job type 1 is 75. Processing times and the setup times at respective machines are given in the following columns. Inter-arrival times of each part are assumed to be exponentially distributed with mean 12 minutes. Jobs are accumulated to form batches of the same type in a defined batch size.

Table 2. Model parameters and input data

			Setup Time (min.) (Triangular distribution)			
Prod. Type	Route	Proc. Time (min)	Starting machine	P1	P2	P3
P1	M3	20	(115,120,125)	0	(105,110,115)	(125,130,135)
	M1	25	(20,25,30)	0	(15,20,25)	(25,30,35)
	M2	30	(25,30,35)	0	(20,25,30)	(30,35,40)
P2	M2	5	(25,30,35)	(20,25,30)	0	(30,35,40)
	M3	15	(95,100,105)	(85,90,95)	0	(105,110,115)
	M4	20	(100,105,110)	(90,95,105)	0	(110,115,120)
P3	M1	10	(20,25,30)	(15,20,25)	(25,30,35)	0
	M4	10	(145,150,155)	(135,140,145)	(155,160,165)	0
	M5	20	(70,75,80)	(60,65,70)	(80,85,90)	0

The model run length and warm-up period is obtained after applying the moving average method. The model is run for 10 runs to obtain the best combination of resources and the best batch size in order to optimize a selected performance measure. The model is tested for different dispatching rules and the corresponding results are obtained. The next section gives the summary of results for different dispatching rules and batch sizes for the corresponding performance measures.

4. Results and Discussion

The developed model is run for various dispatching rules to determine the optimal work center configuration (number of machines at each work center) and the optimal batch size under each rule with respect to average flow time with a maximum of 10 machines at each work center. The rules considered include TWKR-Max (select the batch with the maximum remaining work), TWKR-Min (select the batch with the minimum remaining work), FIFO (Select the first batch arriving), LIFO (select the last batch arriving), SPT (select the batch with the shortest processing time), and LPT (select the batch with the longest processing time). Other measures are also determined for each dispatching rule including the average sum of earliness and tardiness, percentage of jobs tardy, percentage of jobs early, and total jobs completed as shown Table 3.

Table 3. Results for different dispatching rules

Dispatching Rule	**Optimal Resource Configuration**	**Optimal Batch Size**	**% Jobs Tardy**	**% Jobs Early**	**Avg. Flow Time**	**Total Jobs Completed**	**Average earliness and tardiness**
TWKR-Max	9-10-10-10-8	2	62.60	37.40	**255.42**	8954.5	83.34
TWKR-Min	10-10-10-10-10	2	66.63	33.37	**263.52**	8949.5	88.77
FIFO	8-10-10-10-8	2	67.35	32.65	**264.43**	8953.4	88.68
LIFO	8-9-1-10-10	1	66.47	33.53	**155.68**	7000.4	70.60
SPT	10-10-10-10-8	2	63.13	36.87	**257.69**	8975.9	84.56
LPT	10-10-10-10-9	2	65.75	34.25	**262.38**	8961.1	89.02

It is noticeable that optimal batch sizes are small for all dispatching rules and this is due to the high value of job inter-arrival times relative to their processing time. The results show that the last-in-first-out (LIFO) dispatching rule having the minimum average flow time with a value of 155.68 with single unit batches and resource configuration of 8-9-1-10-10 machines for the five work centers. The same rule has also scored the minimum in terms of average total earliness and tardiness. However, the total number of jobs completed using LIFO is low when compared to other dispatching rules. This indicates that LIFO is suitable when considering meeting due dates and minimum in-process storage, but if the main objective is maximizing throughput then any one of the other solutions could be a better choice for batching and dispatching.

It should be noted that the conclusions made here regarding the performance of different dispatching rules is applicable for the data of this example and cannot be generalized for other situations. For example, the performance of the LIFO might not be the best choice if the inter-arrival time was smaller or if the utilization factor was larger. The model should be run with real data, and the choice of the suitable dispatching rule should be made based in its outcome. However, further study is needed for drawing general conclusions regarding the performance of different dispatching rule that is independent of the specific input data.

This model provides the decision maker with immense flexibility in testing different dispatching rules for different conditions. The decision maker can run the model based on one’s requirements or based on one’s budget limits while he/she is trying to optimize a particular performance measure. The budget limits here corresponds to the maximum number of machines that can be made available. The model will then be run with this limitation. Similarly if the main objective is to minimize the number of tardy jobs, then the model should be run with that as the main optimization criteria.

5. Conclusions

A simulation model for resource selection and scheduling was considered for a flexible job shop composed of several work centers and setup time requirement. The optimal number of machines at each center and an optimal batch size for the job shop was determined for sequence dependent setup times. Several dispatching rules were tested for different performance measures. LIFO was found to give the optimal results for both minimizing the average sum of earliness and tardiness, and average flow time, while all other dispatching rules outperformed the LIFO for minimizing the number of tardy jobs.

The developed model can used for deciding upon the number of machines and the way of batching and dispatching for any flexible job shop with similar configuration. Once the data is fed and the primary performance measure is identified, the model can be run for the optimum resource allocation for each dispatching rules along with multiple measures of performance. The decision maker will then make the choice among several performance measures.

Further study is needed for matching dispatching rules and performance measures under general conditions with respect to processing times, interracial times and maximum resource availability. Sensitivity analysis can also be conducted with respect to problem parameters and shop conditions. Having such conclusions will avoid running the model for every possible condition.

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