Dynamic Scheduling of Flexible Manufacturing Systems

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***Abstract*—To date, group scheduling research has primarily focused on examining the performance of different group heuristics under various experimental conditions. However, the dynamic selection of group heuristics has not received sufficient attention from researchers. The objective of this paper is to demonstrate a mechanism for the dynamic selection of group heuristics from several candidate alternatives by exploiting real time information from the Flexible Manufacturing System (FMS). In this regard, two tools, viz., Analytic Hierarchy Process (AHP) and Simple Multi-Attribute Rating Technique Exploiting Ranks (SMARTER), are used to develop models for part type and family selection. The experimental results indicate that the performance of the proposed models are better than the common group scheduling heuristics under varied experimental conditions.**

***Index Terms*-Dynamic scheduling, FMS, AHP, SMARTER**.

I. Introduction

An FMS is designed to combine the benefits of an automated transfer line and the flexibility of a job shop to produce a variety of parts on a group of machines and other workstations connected by an automated material handling system. Some of the advantages of FMS include: improved capital/equipment utilization, substantially reduced throughput times/lead times, reduction in work-in-progress and setups, reduced inventory and smaller batches, and reduced manpower [1, 2]. An FMS is defined as "an integrated manufacturing system that consists of numerically controlled machines equipped with tool magazines and connected by a material handling system, where all system components are under computer control" [3]. Different issues have to be resolved in such an environment for efficient performance, which comprise design, production planning and control. Scheduling plays a vital role in the production control of an FMS, which involves several real-time decisions, such as part type and machine selection, resource allocation, machine allocation, and tool loading. The primary objective of an effective scheduling system is to produce the right parts, at the right time, at a competitive cost, by minimizing overhead and operating costs, subject to satisfying demand for the enterprise's products. Several methods that have been proposed in the literature for scheduling an FMS are summarized in Table I.

TABLE I
FMS SCHEDULING APPROACHES

Approaches	Comments	Ref.
Simulation-based scheduling with dispatching rules	Most common approach in industry. Prioritizes parts when resources are available. Other methods are combined with dispatching rules.	1, 4-6.
Artificial intelligence approaches	AI techniques can handle dynamic and stochastic conditions. Some AI approaches: Expert system (ES), Neural Networks (NN), and Fuzzy logic.	7-11.
Heuristic approaches	Addresses the inability of mathematical solutions in deriving closed form solutions to the FMS scheduling problem. Excellent for dynamic problems. Do not however, guarantee optimal solutions.	12-14.
Schedule permutation	Generates a feasible schedule. Then the initial schedule is systematically permuted and the best schedule is returned after a period of time. Examples include genetic algorithms, simulated annealing, and taboo search.	15-18.
Hybrid approaches	Combine two or more methods. Can handle more computationally complex scheduling problems.	19-21.

Dispatching rules and simulation based tools are preferred for their simplicity, ease of understanding and application. These rules, based on different parameters (such as processing time, set-up time, due date, cost, etc), prioritize parts of different types and the part with the highest priority is assigned to the machine. There is no one universal rule that performs best in all scheduling scenarios. However, dispatching rules do not allow for the use of multiple criteria in the scheduling process and the rigid structure of the dispatching rules excludes the use of

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real-time shop floor conditions and other useful information that may be required for effective scheduling [22]. These rules were designed in the 1950s and do not harness the collective information of other resources. With the recent development of computer technology, such collective information can be easily exploited. In the literature, these simple rules are either modified or grouped with other methods/heuristics to achieve better performance [6, 12]. The research reported in the literature has focused on examining the effects of these rules on the performance of an FMS under various conditions, such as static or dynamic, no routing flexibility or total routing flexibility [1, 4-6]. However, the dynamic selection of group heuristics for scheduling of an FMS has not received adequate attention from researchers. Group scheduling when properly implemented will reduce set-up costs, permit optimal determination of group and part sequence, permit flow line production, optimised group layout, and provide overall economic advantages [24].

In this paper, the scheduling problem is hierarchically decomposed into three distinct levels, comprising of performance measures, performance metrics and candidate heuristics. Besides offering the advantage of genericness, this hierarchical structure also provides a mechanism for directly relating the candidate heuristics to the performance measures through the performance metrics. The dynamic information available in the FMS is reflected in the performance metrics. In other words, the most appropriate scheduling heuristic is selected based on the current environment of the FMS. Two tools are explored in this paper for this purpose, namely the AHP and SMARTER.

In the AHP, simple pairwise comparisons are made at each level throughout the hierarchy to arrive at overall priorities for the alternatives in accordance with the decision maker's preference. The alternative with the highest priority will be selected for scheduling. The SMARTER method employs a systematic procedure in evaluating the attributes from a number of dimensions in a full range. The framework adopted in the developed models is of generic nature, and additional criteria (apart from the demonstrated attributes in this paper) could easily be appended. The rest of the paper is organized as follows. The concept of group scheduling is discussed in the next section. In Section III, the AHP based methodology and the models developed for part and family selection are discussed. In Section IV, the SMARTER based methodology is presented with the details of the two SMARTER models. In Section V, the results are discussed and the paper is concluded with a summary of the key findings in Section VI.

II. Group Scheduling

In group scheduling, the scope of the problem is reduced from a large shop floor to that of a small group of machines. Once the machine groups are identified, each part is then assigned to a particular group for processing and within each group of machines, one only needs to schedule the reduced number of parts that are assigned to that group [24, 25].

Group scheduling heuristics can be classified into two categories: exhaustive and non-exhaustive heuristics. Exhaustive heuristics do not schedule other families until all the parts within the current family are exhausted, while non-exhaustive procedures dynamically evaluate the condition of switching to another family queue [25]. To date, the dynamic selection of group heuristics has not been given due attention in the literature. In this paper exhaustive heuristics are considered for the demonstration of the proposed framework. The group heuristic collectively consists of a family selection heuristic and a part dispatching rule, e.g., MSSPT. The first two letters denote the family selection heuristic and the remaining letters denote the part dispatching rule. In MSSPT, the family with the minimum setup time is chosen, and the part with the shortest processing time in this family's queue is scheduled.

In recent years, two-stage group scheduling heuristics have been increasingly reported and exploited by numerous researchers [26, 27], as they can reduce overall machine setup time by taking advantage of similarities among part families. A typical group scheduling approach involves two stages: the first stage (part selection) involves sequencing parts of different types within each family and the second stage (family selection) consists of determining which family queue to select and when to switch to another family queue at each machine. Fig. 1 illustrates typical decisions that are involved in the group scheduling environment.

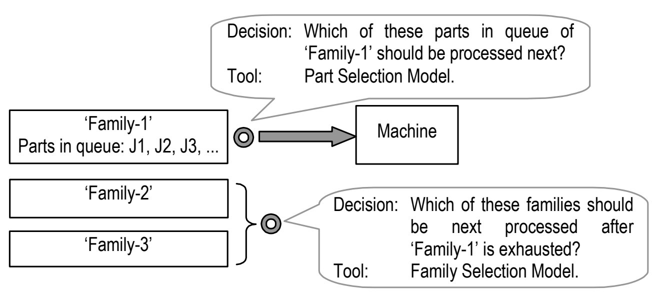

Fig. 1. Typical Decisions in group scheduling

III. AHP Models

The AHP is a powerful and flexible decision making method to set priorities among the alternatives and make the best decision for problems involving multiple objectives when both qualitative and quantitative data are considered. The AHP provides a systematic technique to rank and order feasible alternatives in accordance with the decision maker's preferences [22, 28-29]. By reducing complex decisions to a series of one-on-one comparisons and synthesizing the results, the AHP also provides a clear rationale for the best decision. For its flexibility, simplicity and easy understandability, the AHP has been widely and successfully applied to the problems in electric utility planning, energy policy planning, site selection, education, health care and finance [30]. Two AHP models are developed in this paper, one to sequence the parts of different types within the current family and the other to determine which family queue to be selected when parts within the current family are exhausted.

The solution process employed in the AHP models consists of three levels. At level 1, the performance measures required for the evaluation of the FMS are listed. Normalized weights are assigned to identify the relative importance of these criteria. Two performance measures, namely mean flow time and average cost are used in this paper. These two measures are considered due to their fair representation of the objectives of a typical FMS. At level 2, the performance metrics that influence the performance measures of level 1 are identified. The contributions of each of the metrics towards achieving the overall objective are computed by performing pairwise comparisons (of the metrics) with respect to the performance measures. At the last level, various candidate alternatives (family selection heuristics or part dispatching rules) are identified by performing pairwise comparisons of the alternatives with respect to each of the metrics in level 2. The alternative with the largest resulting weight is then applied to the scheduling problem.

A. The AHP part type selection model

The objective of the AHP part type selection model is to select a part from those that are in queue of the current family. The relative weights of the dispatching rules can be determined at each decision point, and the rule with the highest weightage will be applied to select the next part in the family queue for processing. The AHP model for part type selection is described in Fig. 2, and the pseudocode is as follows:

If *part types* in *current family > 1,*

{

1. For the performance measures **(level 1)**

   {

   Compute the performance weight matrix (PWM) that describes the importance of each performance measure on the fundamental objective.

   }

2. For the metrics **(level 2)**

   {

   Compute the performance metric matrix (PMM) that describes the relative importance of the metrics on the performance measures.

   }

3. For the dispatching rules **(level 3)**

   {

   Compute the dispatching rule matrix (DRM) that describes the normalized priority weights for the dispatching rules.

   }

4. Compute the final priority matrix (FPM), where,

   FPM = DRM × PMM × PWM

   This matrix quantifies the priorities assigned to each dispatching rule.

   Select the dispatching rule with the highest priority.

}

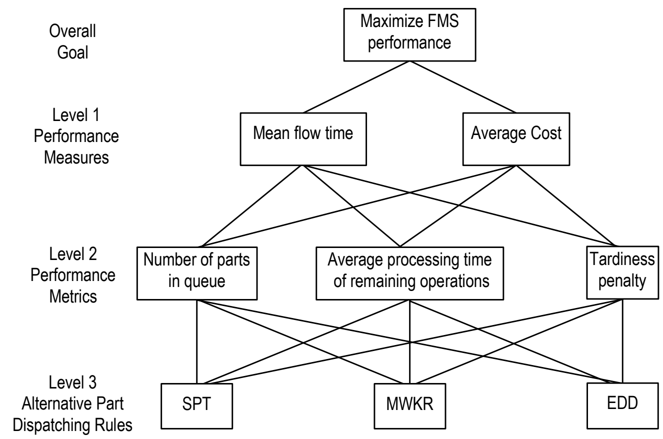

Fig. 2. AHP model for part type selection

At level 2, three performance metrics are identified: *number of parts in queue, average processing time of remaining operations* and *tardiness penalty*. The '*number of parts in queue'* performance metric refers to the queue length of the current family. If the family queue is long, it indicates that the machine has become a bottleneck and the parts in its queue must be quickly processed and dispatching rules that reduce queue lengths, such as shortest processing time (SPT) will be preferred. The '*average processing time of remaining operations*' performance metric is defined as the ratio of the total work remaining of a part to the number of remaining operations of the part. When the ratio is high, it implies that the processing time per part operation remaining is also high, and vice versa. In such instances, the most work remaining (MWKR) dispatching rule would be preferred as this rule will produce good schedules for parts with fewer operations and long processing times. The '*tardiness penalty*' performance metric refers to the tardiness cost, which is computed as the product of the unit tardiness cost and the tardiness of a part. Each part is pre-assigned a unit tardiness cost that reflects the importance of the part. For the same level of tardiness, a part that is required more urgently should reflect a higher tardiness cost than a part for which there is ample inventory and is not urgent. To minimize the tardiness cost, dispatching rules such as EDD (Earliest Due Date) are preferred. Three dispatching rules serve as candidate rules, namely, SPT, MWKR, and EDD.

B. The AHP family selection model

The objective of the AHP family selection model is to select the family to be processed, after all the parts in the current family are exhausted. Through this AHP model, the relative weights of the family selection heuristics can be determined at each decision point, and the heuristic with the highest weight will be applied to select the family. The AHP model for family selection is described in Fig. 3, and the pseudocode is as follows.

If *families* in *queue > 1*

{

1. For the performance measures **(level 1)**

    {

    Compute the performance weight matrix (PWM) that describes the importance of each performance measure on the fundamental objective.

    }

2. For the metrics **(level 2)**

    {

    Compute the performance metric matrix (PMM) that describes the relative importance of metrics on the performance measures.

    }

3. For the family heuristics **(level 3)**

    {

    Compute the family selection heuristic matrix (FHM) that describes the normalized priority weights for alternative family selection heuristics.

    }

4. Compute the final priority matrix (FPM), where,

    FPM = FHM × PMM × PWM

    This matrix quantifies the priorities assigned to each family selection heuristic.

    Select the heuristic with the highest priority.

}

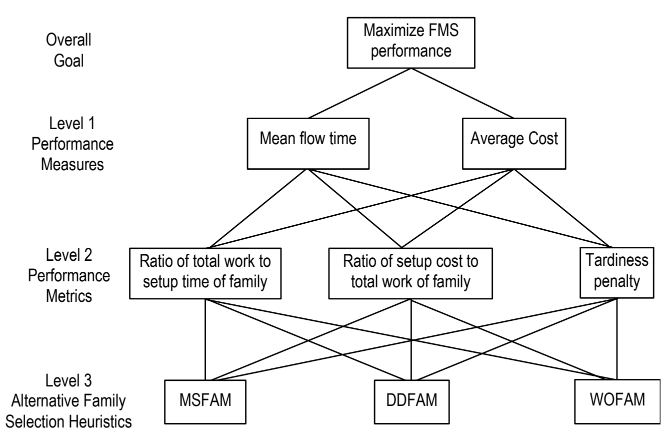

Fig. 3. AHP model for family selection

In level 2, three performance metrics are used: *ratio of total work to setup time of family, ratio of setup cost to total work of family* and *tardiness penalty*. The '*ratio of total work to setup time of family*' performance metric is defined as the ratio of total work content of each family waiting in the machine queue to the setup time of the family. If the ratio is high, it indicates that the setup of the family is more efficient and vice versa. In such instances, the family selection heuristic should select the families with lower setup times and high total work content. The *'ratio of setup cost to total work of family'* performance metric is defined as the ratio of setup cost to the total work content of each family waiting in the machine queue. If the ratio for a family is low, it implies that the setup of the family is cost efficient, and vice versa. The family with the lower ratio is preferred to reduce setup cost and the heuristic selecting this family would be preferred. As previously, the '*tardiness penalty*' performance metric refers to the tardiness cost. To minimize the tardiness cost, the family selection heuristic should select the family whose first part has the earliest due date. Three family selection heuristics are used as candidate heuristics in level 3, viz., MSFAM (chooses the family that requires the minimum amount of setup time), DDFAM (selects the family whose first part has the earliest due date), and WOFAM (selects the family queue with the largest total work content). Note: the letters 'FAM' generically denote the family selection heuristic and is not dependent on the part dispatching rule.

IV. SMARTER MODELS

SMARTER is a modification of the Simple Multi-Attribute Rating Technique (SMART) [31, 32], which provides a mechanism for implementing the principles of multi-attribute utility theory (MAUT). The basic idea of MAUT is that every outcome of an action may have values on a number of different dimensions [33]. MAUT seeks to measure these values one dimension at a time and aggregate these values across dimensions through a weighting procedure. The simplest and most widely used aggregation rule is the weighted linear average formula: $Value_j = \sum w_k.s_{jk}$, where w_k is the weight of the k^{th} dimension and s_{jk} is the measure of alternative j on dimension k. A problem identified in SMART is that the values of weights w_k are related to the values of the single-dimension utilities s_{jk}. SMART Swing weight (SMARTS) was developed to provide swing weights to reflect the full range of possible objective scores. SMART Exploiting Ranks (SMARTER) uses an ordinal approximation to replace the most difficult elicitation (for w_k) step in SMARTS [33].

Two SMARTER models are developed for part and family selection. The mean flow time and average cost performance measures are utilized to evaluate the performance of the FMS. The selected alternatives and metrics should be related to these two performance measures. The following simplified steps are applied to develop the two SMARTER models.

1. Identify the dispatching rules/family selection heuristics as alternatives that are considered for sequencing parts/families, among which one dispatching rule/family selection heuristic is selected for the application.
2. Choose the metrics that influence the alternatives and performance measures. Apply swing weighting and generate relative order for these metrics, e.g. 1,2,3, … (higher to lower). Then normalize these relative values.
3. Calculate scores for each of the identified alternatives (dispatching rule/family selection heuristic) on each metric.
4. Calculate utility for each alternative (dispatching rule/ family selection heuristic) and select the alternative with the maximum utility for sequencing the parts/families.

A. The part selection SMARTER model

This model is used to sequence parts within each family. At each decision point the utilities of the dispatching rules can be determined through the SMARTER model, and the rule with the maximum utility will be applied to select the part in the current family queue.

Three candidate dispatching rules are used in the part selection SMARTER model, viz., SPT, MWKR, and EDD, which are similar to the AHP part selection model discussed in the previous section. Three metrics are considered and these are *Number of parts in queue, Number of remaining operations,* and *Tardiness cost.* If the queue is long, it indicates that the machine has become a bottleneck and the parts in its queue must be quickly processed. Selecting an alternative with a lower number of remaining operations will reduce the total number of parts in the system. Tardiness cost is calculated as the product of the unit tardiness cost and the tardiness of a part. To minimize the tardiness cost, the dispatching rules selecting the part with a higher unit tardiness cost are preferred. Based on the pilot experiments on swing weighting, it is found that the following relative order of metrics will yield good overall performance: *Number of parts in queue > Number of remaining operations > Tardiness cost.*

According to the operations of the SMARTER method, the normalized metric weights are generated as follows.

W_1 (*Number of parts in queue*) : (1 + 1/2 + 1/3) / 3 = 0.61
W_2 (*Number of remaining operations*) : (0 + 1/2 + 1/3) / 3 = 0.28
W_3 (*Tardiness cost*) : (0 + 0 + 1/3) / 3 = 0.11

The score of an alternative will be calculated on a 0-100 scale, with 0 and 100 as the minimum and maximum plausible values respectively. If the metric is measured on a continuous scale, we can use formulae to convert the value of the metrics onto a 0-100 scale. For the case of metrics that are evaluated using a cost function, the conversion formula is defined as:

$$score_{j,k} = 100(\max_k - Value_j)/(\max_k - \min_k) \quad (1)$$

where $score_{j,k}$ and $Value_j$ are the score and value of alternative j on metric k respectively, and $\max_k$, $\min_k$ are the maximum and minimum values of all alternatives of metric k. For metrics that are evaluated using a profit function, the conversion formula is defined as:

$$score_{j,k} = 100(Value_j)/(\max_k - \min_k) \quad (2)$$

In the model, both *'number of remaining operations'* and *'tardiness cost'* are measured on a continuous scale. On the other hand, *'number of parts in queue'* is not measured on a continuous scale. For example, if there are eight parts for each family, the maximum queue length of each family is eight and we assume that any family queue with three or more parts will be considered as long. For a long queue, we shall prefer SPT to the other rules, and based on pilot runs, we find that good overall performance is achieved when the score of SPT on this metric is 60 and the scores of MWKR and EDD are 40. If the family queue is not long, the candidate rules are equally preferred and in this case, the scores of the candidate rules are all identical, so the values will not affect the results. In such situations, an equal score of 40 for all candidate rules will be assumed.

Utilities can be obtained by applying the formula: $U_j=\sum w_k.s_{jk}$. For example, at a decision point, assume that the scores of alternatives on metrics have been calculated as follows:

Alternative	*Number of parts in queue*	*Number of remaining operations*	*Tardiness cost*
Weights	0.61	0.28	0.11
SPT	60	68.3	58.3
MWKR	40	75.0	41.7
EDD	40	50.0	45.8

Then the utilities are computed as follows:

SPT : 0.61(60) + 0.28(68.3) + 0.11(58.3) = 62.1
MWKR : 0.61(40) + 0.28(75.0) + 0.11(41.7) = 50.0
EDD : 0.61(40) + 0.28(50.0) + 0.11(45.8) = 43.4

The dispatching rule SPT has the highest utility and thus it will be used for part selection.

B. The family selection SMARTER model,

The purpose of the second SMARTER model is to select the family to be processed, after all the parts in the current family are exhausted. The utilities of the family selection heuristics can be determined at each decision point through the model and the heuristic with the maximum utility will be applied to select the family.

Three exhaustive family selection heuristics are selected as alternatives: MSFAM, DDFAM, and WOFAM. Five metrics are utilised in this model: *Setup time of family, Due date of family, Tardiness cost, Total work of family,* and *Unit setup cost of family.* Based on our experience and pilot experiments, the following relative order of metric will yield good overall performance: *Setup time of subfamily > Due date of subfamily > Unit tardiness cost > Total work of subfamily > Unit setup cost of subfamily.*

The normalised metric weights are generated as follows:

W_1 (*Setup time of family*): (1 + 1/2 + 1/3 + 1/4 + 1/5) / 5 = 0.46
W_2 (*Due date of family*): (0 + 1/2 + 1/3 + 1/4 + 1/5) / 5 = 0.26
W_3 (*Tardiness cost*): (0 + 0 + 1/3 + 1/4 + 1/5) / 5 = 0.15
W_4 (*Total work of family*): (0 + 0 + 0 + 1/4 + 1/5) / 5 = 0.09
W_5 (*Unit setup cost of family*): (0 + 0 + 0 + 0 + 1/5) / 5 = 0.04

All metrics in this model are measured on a continuous scale, so scores for each alternative on each metric can be computed using equations (1) or (2). The calculation of utility of each alternative is the same as that described for the part selection SMARTER model.

V. RESULTS AND DISCUSSION

A. Details of the FMS model

The hypothetical FMS examined in this paper is a modification of the model presented in [20], and is illustrated in Fig. 4. A machine is added to the original model and the process plans are slightly altered. The FMS is composed of two CNC machines, two machines and two robots for loading/unloading parts. The I/O station contains both the parts of different types and families waiting to enter the FMS and the completed parts are removed from the FMS by an automated guided vehicle. The capacity of the I/O station is assumed to be large, and each machine has an intra-cell buffer. A central conveyor moves bi-directionally to transport parts between the two robots.

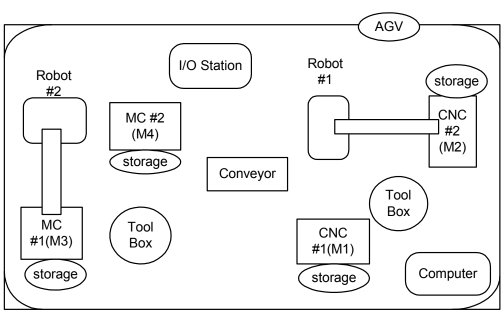

Fig. 4. The modified FMS [20]

A part entering the FMS can be classified according to its family and part type. There are three families to be processed by this FMS. Each of these families consists of eight distinct part types. For simplicity, it is assumed that the part types in different families have the same routings, i.e. all parts of type 1 irrespective of family 1, 2 or 3 have similar routings. The sequence of operations for each part is fixed, but each part may have a choice of routes, a basic and an alternate route. The details of the basic and alternate routes (process plans) for the eight part types of the families are presented in Table II. When the basic machine is not available, or has too many parts waiting in its queue, the part will adopt its alternate machine.

TABLE II
PROCESS PLANS FOR EIGHT PART TYPES

Operation → Part Type ↓	1	2	3	4
J1	M1/M2	M4/M3	M2	
J2	M2/M3	M1		
J3	M3/M4	M4/M1	M4	
J4	M4	M3	M2/M1	M2/M3
J5	M4/M3	M2/M4	M1	
J6	M1/M4	M2	M3/M2	
J7	M3/M1	M2/M3	M4	
J8	M1	M3/M2	M1/M3	M4

(Mp/Mq = the basic machine required for processing / the alternative machine required for processing).

The arrival of parts into the system is modeled as an exponential distribution. The processing times of the operations follow a third-order Erlang distribution with means of 15 minutes and 17.5 minutes for their basic and alternate machines respectively. The transportation times are considered to be negligible. Due dates are assigned to the parts as they enter the FMS. The due date of part j, is defined as: $d_j = a_j + U[T_l,T_u]$; where a_j is the arrival time of part j, T_l and T_u are lower and upper limits of a Uniform distribution. The setup times and setup costs are considered to be sequence dependent. The setup times are modeled as a second-order Erlang distribution since setup times are generally more variable than the processing times. The setup time of each part in a family is assumed to be negligible compared to the setup time of a family. In addition, the setup costs are modeled as a uniform distribution. Unit tardiness costs of parts are uniformly distributed between \$0.1 and \$1.5 per minute. The unit processing cost of each machine is fixed at \$0.9 per minute for M1 and M2 and \$1.0 per minute for M3 and M4.

B. Experimental factors

The simulation study proposed in this paper requires several parameters/factors to be set. However, only a few of them are expected to influence the relative performance of the proposed framework over the other scheduling heuristics. We have therefore confined this study to three important factors, and these are varied to study the performance of the proposed framework and other scheduling heuristics under various operating conditions. Each factor is considered at two levels (namely high and low), and these experimental factors are:

Setup time to run time ratio: This factor is considered since the primary justification for group scheduling heuristics is setup reduction. This is defined as the ratio of mean setup time to mean operation processing time. Clearly, this factor varies widely from one industry to another and thus its inclusion can aid in determining the desirability of the group scheduling heuristics. The average setup time to run time ratios are set at 0.5 and 1.0 for the low and high levels.

Workload: This factor is considered to examine the effect of workload on the performance of the proposed models and heuristics. Different workload levels, measured by bottleneck utilization, are achieved by varying the inter-arrival times. The inter-arrival times are determined by pilot runs, so that a bottleneck utilization of 80% and 85% are realized at the low and high levels of workload respectively. These bottleneck utilization rates are obtained using the FCFCFS group scheduling heuristic (*first come first serve* for both part selection and family selection) and the bottleneck utilization is the maximum utilization of the machines.

Due date tightness: This factor is considered because recent surveys have concluded that the responsiveness of manufacturers has become increasingly important [18]. Therefore, due date tightness levels are established by pilot runs so that approximately 20% and 50% of the parts become tardy under the FCFCFS heuristic for loose and tight due dates. The loose and tight due dates can be achieved by adjusting T_l and T_u.

C. Details of experiments

The simulation is developed in SIMSCRIPT II.5, using a combined process and event orientation [34]. The initial state of the system is empty and idle, and brought to steady state by a warm-up period of 60,000 minutes. Statistics are collected for 120,000 minutes after the warm-up period. Fifty replications are produced to achieve the sufficient precision required to estimate the mean differences in performance [26]. To examine the performance of the heuristics, the three experimental factors discussed previously (namely: setup time to runtime ratio, workload, and due date tightness) are varied at two levels: high and low, thereby spanning a full factorial (2^3) experiment. For evaluation purposes, the framework discussed in this paper are compared with common group scheduling heuristics. In this respect, we have identified three family selection heuristics (MSFAM, DDFAM and WOFAM) and three part dispatching rules (SPT, EDD and MWKR). Therefore, nine (3 × 3) combinations of group scheduling heuristics are possible and they are: MSSPT, MSEDD, MSMWKR, DDSPT, DDEDD, DDMWKR, WOSPT, WOEDD and WOMWKR.

D. Results

The performance of the AHP and SMARTER models are evaluated with respect to the group scheduling heuristics under varied conditions (2^3 experimental combinations). The results of the simulation study are summarized in Table III. Hypothesis tests are conducted for the differences among mean responses. A series of paired *t*-tests are conducted to statistically rank the various approaches. Generally, with N scheduling heuristics, $K = N(N-1)/2$ pairwise comparisons are performed for each of the performance measures. Thus according to the Bonferroni inequality, if an overall significance level of α percent is desired, each individual test should be significant at α/K percent level. In the statistical analysis, an overall confidence level of 95 percent is assumed ($\alpha = 0.05$). The results indicate significant differences among the heuristics. These results are summarized in Tables IV and V. In these tables, the heuristics are listed in order of their performance (best to worst), and those connected symbolically do not exhibit statistically significant performance differences. The performance of the heuristics is further analyzed in greater detail for each of the performance measures.

TABLE III
RESULTS

Method	HL, HS, TD		HL, HS, LD		HL, LS, TD		HL, LS, LD	
	MFT	AC	MFT	AC	MFT	AC	MFT	AC
MSSPT	156.12	81.03	155.93	67.73	135.71	70.07	135.40	58.73
MSEDD	159.95	78.95	159.96	66.20	141.04	68.26	140.71	57.28
MSMWKR	157.14	81.57	157.03	68.64	137.12	71.11	136.70	59.45
DDSPT	162.80	78.07	162.95	67.10	139.73	68.74	140.14	58.40
DDEDD	168.40	76.73	167.14	65.50	147.64	66.99	146.60	57.10
DDMWKR	163.46	78.42	164.14	67.94	141.38	69.42	140.84	59.08
WOSPT	162.15	81.19	162.15	69.02	139.78	70.15	139.78	59.14
WOEDD	167.14	79.73	167.63	67.11	146.60	68.81	147.05	58.33
WOMWKR	162.81	81.62	163.07	68.58	141.37	71.01	141.37	60.05
AHP	156.35	75.48	155.27	64.60	135.98	66.52	136.11	56.89
SMARTER	155.62	76.58	155.27	65.31	135.98	67.26	136.21	57.64

Method	LL, HS, TD		LL, HS, LD		LL, LS, TD		LL, LS, LD	
	MFT	AC	MFT	AC	MFT	AC	MFT	AC
MSSPT	147.30	81.14	147.27	68.08	123.76	70.07	124.01	59.08
MSEDD	149.70	79.26	149.70	66.79	126.77	68.31	126.77	57.96
MSMWKR	148.23	81.64	147.90	68.55	124.52	70.82	124.74	59.58
DDSPT	152.40	78.68	152.46	67.09	127.25	68.37	127.13	58.67
DDEDD	155.61	77.70	155.74	66.43	130.91	67.23	131.14	57.72
DDMWKR	153.31	79.84	152.90	67.56	128.30	69.28	127.76	59.11
WOSPT	151.61	81.17	151.61	68.79	126.87	70.07	126.87	59.44
WOEDD	155.13	79.69	155.13	67.62	130.82	68.67	130.82	58.62
WOMWKR	152.37	81.92	152.45	69.36	127.64	70.97	127.64	60.50
AHP	147.19	76.35	146.22	65.31	123.84	66.51	123.48	57.00
SMARTER	146.92	77.35	146.87	66.13	123.56	67.14	123.63	57.71

HL – high load, LL – low load, HS – high setup to runtime ratio, LS – low setup to runtime ratio, TD – tight due date, LD – low due date, MFT – mean flow time, AC – average cost.

E. Discussion

Mean Flow Time: For mean flow time, the AHP and SMARTER models perform better than the common group heuristics under most of the experimental conditions. This is expected since the developed models consider both processing time and setup time at each decision point and dynamically select the group heuristic with the highest priority to reduce mean flow time. MSFAM (comprising of MSSPT, MSMWKR, and MSEDD) dominates all other family heuristics regardless of the dispatching rules. WOFAM (comprising of WOSPT, WOMWKR, and WOEDD) is the second best heuristic under all experimental conditions and DDFAM (comprising of DDSPT, DDMWKR, and DDEDD) has the worst performance. The dispatching rules also have a major impact on the performance of the family selection heuristics. Within the same queue, the SPT and MWKR part selection heuristics exhibit better performance than EDD. After the AHP and SMARTER models, MSSPT and MSMWKR are the best performing heuristics under all experimental conditions while WOEDD and DDEDD generally exhibit the poorest performance.

Average Cost: For average cost, the AHP models outperforms under all experimental conditions. The AHP models consider processing cost, setup cost and tardiness cost simultaneously and dynamically select the group heuristic with the highest priority to reduce total cost. The SMARTER models also performed well, and ranked next to the AHP under most of the experimental conditions. DDFAM (comprising of DDSPT, DDMWKR, and DDEDD) dominates the other family heuristics under all experimental conditions. The WOFAM (comprising of WOSPT, WOMWKR, and WOEDD) heuristic performs the worst. After the AHP, DDEDD is the best performing heuristic under all experimental conditions, and generally DDSPT performs the second best for tight due dates while MSEDD performs the second best for the loose due dates.

VI. CONCLUSIONS

In this paper an attempt has been made to develop and demonstrate a framework for the dynamic scheduling of an FMS. This framework considers the prevalent conditions at each decision point and dynamically select the most suitable group heuristic (collectively consisting of a family selection heuristic and a part dispatching rule). The performances of the models are compared with nine group heuristics. The results indicate that the proposed models exhibit better performance than group scheduling heuristics individually, under nearly all the experimental conditions. The framework proposed in this paper is a general one and additional criteria (such as schedule length, maximum lateness, etc.) may be easily added. In addition, the framework can also be modified to account for other factors such as the unreliability of machines.

TABLE IV

PAIRED T-TEST RESULTS FOR MEAN FLOW TIME

HL,HS,TD	HL,HS,LD	HL,LS,TD	HL,LS,LD	LL,HS,TD	LL,HS,LD	LL,LS,TD	LL,LS,LD
SMARTER	SMARTER	MSSPT	MSSPT	SMARTER	SMARTER	SMARTER	AHP
MSSPT	AHP	SMARTER	AHP	AHP	AHP	MSSPT	SMARTER
AHP	MSSPT	AHP	SMARTER	MSSPT	MSSPT	AHP	MSSPT
MSMWKR	MSMWKR	MSMWKR	MSMWKR	MSMWKR	MSMWKR	MSMWKR	MSMWKR
MSEDD	MSEDD	DDSPT	WOSPT	MSEDD	MSEDD	MSEDD	MSEDD
WOSPT	WOSPT	WOSPT	DDSPT	WOSPT	WOSPT	WOSPT	WOSPT
DDSPT	DDSPT	MSEDD	MSEDD	WOMWKR	WOMWKR	DDSPT	DDSPT
WOMWKR	WOMWKR	WOMWKR	DDMWKR	DDSPT	DDSPT	WOMWKR	WOMWKR
DDMWKR	DDMWKR	DDMWKR	WOMWKR	DDMWKR	DDMWKR	DDMWKR	DDMWKR
WOEDD	DDEDD	WOEDD	DDEDD	WOEDD	WOEDD	WOEDD	WOEDD
DDEDD	WOEDD	DDEDD	WOEDD	DDEDD	DDEDD	DDEDD	DDEDD

Symbolic links denote insignificant difference in the ranking of the heuristics.

TABLE V

PAIRED T-TEST RESULTS FOR AVERAGE COST

HL,HS,TD	HL,HS,LD	HL,LS,TD	HL,LS,LD	LL,HS,TD	LL,HS,LD	LL,LS,TD	LL,LS,LD
AHP	AHP	AHP	AHP	AHP	AHP	AHP	AHP
SMARTER	SMARTER	DDEDD	DDEDD	SMARTER	SMARTER	SMARTER	SMARTER
DDEDD	DDEDD	SMARTER	SMARTER	DDEDD	DDEDD	DDEDD	DDEDD
DDSPT	MSEDD	MSEDD	MSEDD	DDSPT	MSEDD	DDSPT	MSEDD
DDMWKR	DDSPT	DDSPT	WOEDD	MSEDD	DDSPT	MSEDD	WOEDD
MSEDD	WOEDD	WOEDD	DDSPT	WOEDD	DDMWKR	WOEDD	DDSPT
WOEDD	MSSPT	DDMWKR	MSSPT	DDMWKR	WOEDD	DDMWKR	MSSPT
MSSPT	DDMWKR	MSSPT	DDMWKR	MSSPT	MSSPT	MSSPT	DDMWKR
WOSPT	WOMWKR	WOSPT	WOSPT	WOSPT	MSMWKR	WOSPT	WOSPT
MSMWKR	MSMWKR	WOMWKR	MSMWKR	MSMWKR	WOSPT	MSMWKR	MSMWKR
WOMWKR	WOSPT	MSMWKR	WOMWKR	WOMWKR	WOMWKR	WOMWKR	WOMWKR

Symbolic links denote insignificant difference in the ranking of the heuristics.

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