A Fuzzy Logic Decision Support Algorithm for Multi-cell Flexible Manufacturing Systems

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ABSTRACT

Because of the nature of conventional 0-1 part-family incidence matrix, a multi-cell flexible manufacturing systems (MCFMS) using conventional part-family formation algorithms, such as array-based clustering, similarity coefficient-based clustering, and mathematical programming, in a cellular manufacturing mode can assign a part family only to one machine cell. The consequence is that each part type has a fixed route through the system. When each part family is limited to a fixed route through the system, the performance of an MCFMS is diminished. This is because the inherent flexibility of the MCFMS is not fully utilized. This research proposes a fuzzy dynamic routing method that applies a fuzzy clustering algorithm combined with a certainty factor procedure to suggest the favorable route in an MCFMS. Computational simulations show that the proposed dynamic routing method that seeks to balance workload in an MCFMS is more effective than the fixed routing method in reducing mean flowtime, mean tardiness, and mean absolute lateness, in an environment characterized by high system utilization (85% or higher) and under a variety of demand patterns and machine breakdowns.

1. INTRODUCTION

A multicell flexible manufacturing system (MCFMS) is a type of FMS which consists of a number of flexible manufacturing cells (FMCs) connected by an automated material handling system (MacCarthy and Liu 1993). The major advantage of MCFMS is setup time reduction. This is because setups can be simplified by dedicating the machines in a cell to a part family with similar processes. Other advantages include: reduction in work-in-process inventory (WIP) and in manufacturing lead time (Greene and Sadowski 1984), and easier to manage workers, tools, pallets, ... ect. due to the limited size of each machine cell (Kusiak and Heragu 1987, O'Grady 1989). In addition, the transformation from traditional job shop to MCFMS may result in increased operator responsibility and increased job satisfaction, both of which can increase product quality and worker productivity (Garza and Smunt 1991).

A main disadvantage of MCFMS is a loss of process flexibility in dealing with job mix and demand changes which lead to a workload imbalance in the system (Ang 1995). This is because MCFMS dedicates specific machines to the manufacture of part families. Other disadvantages of MCFMS are the increased capital necessary for additional machines and tools (Garza and Smunt 1991).

In a recent research, Ang (1995) proposed an inter-cell workload transfer strategy to overcome the problems caused by the loss of process flexibility in MCFMS and to improve shop performance by transferring workload from a congested cell to an alternative, less congested cell. The effect of the inter-cell workload transfer is comparable to alternative routing both of which can improve load distribution of shop floor (Ang 1995). The results have shown that with a small number of inter-cell transfers the performance of the MCFMS can be significantly improved.

On the other hand, Garza and Smunt (1991) found that even small amounts of inter-cell flow can have a substantial negative impact on mean flow times and WIP in a manufacturing cell. In their experiments, Garza and Smunt considered inter-cell flow not only as a result of alternative routings in the shop but as the lack of processing capability within a cell. The research tested both the effect of inter-cell flow and the effect of machine dedication under a wide range of conditions.

In a very recent research, Wen, Smith, and Minor (1996) suggested that inter-cell flow, as a result of alternative routing, has positive impact on MCFMS performance under high system utilization but has negative impact under low system utilization. Since routing among FMCs does not always benefit the shop performance, it is important in practice to make a proper intercell routing decision. A right routing decision potentially improves performance by eliminating the bottlenecks that often present when alternate routes are not feasible. In this research we proposed a fuzzy dynamic routing method which suggests an intercell routing based on the current workload of FMCs and changes in the operating conditions. The proposed dynamic routing method is simple, and allows for locally revising schedules in real time.

2. THE PROPOSED DYNAMIC ROUTING METHOD

Routing in MCFMSs differs from that in a conventional job shop because of the availability of alternative resources resulting in routing flexibility both within an FMC and among FMCs. The proposed dynamic routing method uses a fuzzy part-family formation method, which identifies routing options among FMCs. To select the preferred route the method generates certainty factors that provide scores for the alternative routes.

Fuzzy Part-Family Formation

A conventional manufacturing cell is capable of processing only a fixed number of part types; thus, conventional part-family formation methods are not appropriate for FMCs. The conventional methods, such as array-based clustering (King 1980, King and Nakornchai 1982), similarity coefficient-based clustering (McAuley 1972, Seifoddini and Wolfe 1986), and mathematical programming (Kusiak 1987; Gunasingh and Lashkari 1989), can assign a part to only one machine cell. Thus, each part type has a fixed route through the system, as shown in Figure 1. When each part is limited to a fixed route through the system, the performance of an MCFMS is diminished because the inherent flexibility of the FMS is not fully utilized (Chen and Chung 1991).

Figure 2 illustrates that a fuzzy part-family method that assumes part families are not mutually exclusive allows for dynamic routing of part families among FMCs. The rescheduling method we propose provides priorities for all the possible routes among FMCs. Route priority is based on the "degree of membership" of a part in the various part families associated with cells. For example, the first routing priority for P1 is cell 2 because it has the highest degree of membership (.7) associated with family 2 and the second (.2) and third (.1) routing priorities are cell 1 and cell 3, respectively.

All the conventional part-family formation methods implicitly assume part families are mutually exclusive and collectively exhaustive (Li and Ding 1988; Xu and Wang 1989; Chu and Hayya 1991). Suppose that *n* parts are to be grouped into *c* families. The conventional methods assume that disjoint part families exist in the data set; therefore, a part can only belong to one part family. The classification results, thus, can be expressed as a binary matrix such as illustrated in Figure 2, where n is the number of parts and c is the number of families, with $n \geq c$. It is also required that each matrix entry $u_{ij} = 0$ or 1, and

$$\sum_{i=1}^{c} u_{ij} = 1, \quad j=1,2,...,n \tag{1}$$

$$\sum_{j=1}^{n} u_{ij} > 0, \quad i=1,2,...,c \tag{2}$$

These requirements insure that u_{ij} equals 1 if the *jth* part belongs to the *ith* part family, each part belongs to exactly one part family, and each part family consists of at least one part.

However, part families need not be defined so sharply; rather, the separation of part families is often fuzzy. Suppose variable u_{ij} may have any value between 0 and 1; that is, a part may belong to several part families at the same time with different degrees of membership. In fuzzy clustering, the classification results can be expressed as in Figure 2, where

$$0 \le u_{ij} \le 1, \quad i=1,2,...,c; \quad j=1,2,...,n \tag{3}$$

and constraints (1) and (2) still apply.

The fuzzy c-means clustering algorithm is adapted in this paper to handle the cell formation problem. The clustering algorithm is based on distance from the clustering center, a smaller distance associated with a higher degree of membership. The clustering algorithm is now briefly discussed below.

Let p is the number of machines and let $\mu_k(x_{jk})$ be the 0 or 1 representing the relationship of the j^{th} part to the k^{th} machine. The $1 \times p$ vector V_i is created to serve as the representative point for parts in the i^{th} part family.

$$V_i = (v_{i1}, v_{i2}, ..., v_{ip})$$

where

$$v_{ik} = \frac{\sum_{j=1}^{n} u_{ij} \times \mu_k(x_{jk})}{\sum_{j=1}^{n} u_{ij}}$$

$$i = 1, 2, ..., c; \quad k = 1, 2, ..., p$$

The distance of the j^{th} part from the i^{th} part family is:

$$\left\{ \sum_{k=1}^{p} \left(\mu_k(x_{jk}) - v_{ik} \right)^2 \right\}^{\frac{1}{2}}$$

and weighted sum of squares of the distance of the j^{th} part from the C part families is:

$$\sum_{i=1}^{c} u_{ij} \sum_{k=1}^{p} \left(\mu_k(x_{jk}) - v_{ik} \right)^2$$

The total weighted sum of squares of the distance of n parts from the C part families is:

$$J(U,V) = \sum_{j=1}^{n} \sum_{i=1}^{c} u_{ij} \sum_{k=1}^{p} \left(\mu_k(x_{jk}) - v_{ik} \right)^2$$

In order to increase the distance between sample reference patterns, a weighting coefficient m (m>1) can be used here:

$$J_m(U,V) = \sum_{j=1}^{n} \sum_{i=1}^{c} u_{ij}^{m} \sum_{k=1}^{p} \left(\mu_k(x_{jk}) - v_{ik} \right)^2$$

An algorithm (Lou, Sun, and Chen 1983) for minimizing the objective function is given as follows:

$$u_{ij} = \frac{1}{\sum_{l=1}^{c}\left(\frac{\sum_{k=1}^{p}\left(\mu_k(x_{jk}) - v_{ik}\right)^2}{\sum_{k=1}^{p}\left(\mu_k(x_{jk}) - v_{lk}\right)^2}\right)^{2/(m-1)}}$$

Based on the final fuzzy classification matrix *U*, part *j* is assigned to family *i* if

$$u_{ij} = \max_{1 \le k \le c} \{u_{kj}\}$$

The fuzzy clustering approach not only reveals the specific part family (or FMC) that a part (or machine) belongs to, but also provides the degree of membership of a part (or machine) associated with each part family (or FMC). As illustrated in Figure 2, the fuzzy clustering algorithm produces a machine cell-part membership matrix. The values in the table indicate the degree of membership of each part in each part family or FMC. For example, the grades of membership for part 2 in FMC-1 and FMC-3 are .60 and .40. Since part 2 has the higher grade with FMC-1, it will be assigned to FMC-1. However, because part 2 has a fairly large grade with FMC-3, it could, if needed, also be assigned to FMC-3 under certain conditions, such as a machine breakdown in FMC-1 or an unusually high demand for part family 1.

In summary, the fuzzy clustering algorithm provides extra information that is not available in conventional algorithms. This information permits managers to make more informed dynamic routing decisions by allowing for flexible assignment of parts to FMCs. The information would be especially useful in balancing FMCs workloads. The 'degree of membership' is somewhat equivalent to 'degree of effectiveness' with which any part can be produced within a given FMC; the higher the degree of membership, the higher the degree of effectiveness. Certainty factors, as described in the next section, provide a real-time basis for selecting effective routing alternatives.

3. THE SIMULATION MODEL

The purpose of this simulation is to compare the performance of the proposed dynamic routing method with the performance of the fixed routing method under a variety of conditions. The system under study is similar to the one studied by Seifoddini (1989) and Wen et al (1996). The machine-part incidence matrix used to group machine cells and form part families is given in Table 2.

The fuzzy c-means clustering algorithm was coded in SAS Interactive Matrix Language (IML). The degrees of membership of parts associated with part families and machines associated with machine cells are given in Table 3. The machine cells and part families are formed accordingly. The FMC-1 consists of machines A, B, D, E, F, and K and parts 1, 2, 3, 5, 7, 8, 11, 12, 15, 16, 19, 20, 21, and 22. The FMC-2 consists of machines C, G, H, I, and L and parts 4, 6, 9, 10, 13, 14, 17, and 18. Part #5, for example, belongs to part family 1 with .53 degree of membership and to part family 2 with .47 degree of membership. In FMS implementation, both cell 1 and cell 2 are feasible routes for part #5, but generally machine cell 1 is the favorable route. Notice that the part families for both the dynamic routing approach and the fixed routing approach are the same, determined using the fuzzy c-means clustering algorithm. The difference is that the dynamic routing approach will allocate parts into different machine cells based on current certainty measures.

Extensive details of the configuration of the simulated system are provided in Table 4. A simulated model of the FMS described above was developed using SLAM II (Pritsker 1995). Part interarrival times are exponentially distributed. Each part is processed by a series of machines. The number of operations per part is between 2 and 7 as shown in Table 2, and the processing times of operations range from 30 minutes to 50 minutes. The tooling system is not modeled, and an infinite number of pallets are assumed. Buffer capacity at each cell is unlimited. Thus, a part completing a current operation waits in the buffer at the cell until an AGV is available. An AGV transfers only one part at a time, and time to travel between any two machines is the same. There is only one AGV in each machine cell. The dispatching rule is FCFS.

The experimental conditions used to compare the two routing methods included six system utilization levels, two demand patterns, and a machine breakdown scenario. Machine utilization rates commonly found in the literature are in the 75% to 90% range. This paper evaluates the routing methods at 70%, 75%, 80%, 85%, 90% and 95% utilization. In the normal case demand pattern all parts are equally likely to be selected as the next arrival to the system. In one of the alternative demand patterns the workload is altered to favor arrival of parts with particularly high degrees of membership in their part families, high-fit parts. The remaining demand pattern biases the workload towards parts with low degrees of membership in their part families, low-fit parts. Machines are randomly selected for breakdown. A machine breakdown occurs in the system on an average of every 50 minutes (exponentially distributed), with each breakdown lasting 60 minutes. A total of 480 simulation runs (two routing policies × two demand patterns × a machine breakdown scenario × six system utilization levels × 20) were made.

The length of the transition period can be determined by plotting measures such as the number of parts waiting at the bottleneck machines over time (Adiga and Dessouky 1991). The average number of parts waiting at machines C, D, K, and L (which are busier machines) were plotted over time. System steady state was considered to have occurred before 200 orders. For each simulation run data is collected on 1000 orders after statistics for the first 200 part orders are discarded. Therefore, each simulation run comprises 1,200 jobs.

In these experiments due dates of jobs were determined by allocating allowances to a job for the performance of its various operations. The type of due date assignment that allows the producer the freedom to set due dates is known as endogenous due date assignment. Sabuncuoglu and Hommertzheim (1992) found the TWK (total work content) rule effective, and it has been widely used in job shop studies. The TWK rule was used to set the part due dates as explained in Table 4.

Several criteria have been used in FMS research to measure shop performance. Due date performance and reduction of average inventory level are commonly stressed in today's manufacturing environment, and the three performance measures used in this research reflect this emphasis. Mean flowtime, mean tardiness, and mean absolute lateness of part orders are reported. Lower mean flowtimes indicate reduction in average inventory. Mean absolute lateness measures reliability in completing orders near the due date by penalizing both early and late completion. Mean tardiness has been the most popular measure of due date performance in the published literature, indicating the average time beyond the due date for order completion.

4. RESULTS AND ANALYSES

In order to detect significant differences due to the influence of different routing methods, we perform paired comparison between the values of performance measures, namely, flowtime, tardiness, and absolute lateness. Carmer and Swanson (1973) conducted extensive Monte Carlo simulation studies of several multiple comparison methods. They reported that the least significant difference (LSD) method is a very effective test for detecting true differences in means if applied only after the ANOVA F-test is significant at $p \leq .05$. In this study, we use the LSD method for paired comparisons of the mean values of the performance measures. The statistical analysis in this study was conducted using SAS, version 10.12. All the tests were conducted at the 0.05 level of significance. Raw data obtained from the simulations were fed into the computer. In a pilot run, the mean values and the variances of the performance measures were computed for 85% system utilization. ANOVA results on these data appear in Table 5. All three analyses indicate that significant differences between dynamic routing and fixed routing methods exist. As can be seen, all three performance measures are significant at $p \leq .0001$ confidence level.

To confirm or disprove the statistical results that the proposed dynamic routing method outperforms the fixed routing method at 85% utilization level, we do two more tests, in which the dynamic routing decisions are made with *wrong* and *random* degree of membership. The purpose of these tests is to see whether the correct degree of membership is the major factor affecting the quality of the dynamic routing decision making. If there are no significant differences between the dynamic routing method using correct, wrong and random degree of membership, we may disprove the previous finding that the proposed method works better.

The results are shown in Table 6. As can be seen, the right degree of membership does help to make a good dynamic routing decision, which improved the mean flowtime performance. Therefore, we conclude that the proposed dynamic routing method outperforms the fixed routing method at 85% system utilization level.

4.1 Different Machine Utilization Levels

Figure 3, 4, and 5 clearly suggest that there is a performance switching point between the routing methods for all three performance measures. The performance switching point is where the system performance switches from favoring fixed routing to dynamic routing. In this experiment, the switching point is at between 80% and 85% system utilization.

For alternative system utilization levels the mean flowtimes are shown in Figure 3 for both the proposed dynamic routing method and the fixed routing method. In general, as the system utilization increased, the relative performance of the dynamic routing method improved. For example, at 85%, 90%, and 95% utilization levels, approximately 29%, 32%, and 19%

reductions in the mean flowtime were achieved by the dynamic routing method. However, at 70%, 75%, and 80% utilization the fixed routing method showed better flowtime performance. This observation can be explained. At the low utilization level, there are fewer jobs in the queues. As long as the machines are at low utilization, parts should have shorter flowtimes when processed in the cells designed for their own part families. Any procedure that can assign parts to another cell may harm mean flowtime performance. On the other hand, at a high utilization level the dynamic routing method worked better because the workload was reduced in the busier cell, resulting in fewer long queues.

Figure 4, and 5 also show the mean tardiness and mean absolute lateness of the routing methods at varying levels of system utilization, when the due date allowance parameter is ten (i.e., due date of a part is ten times greater than its total processing time); this resulted in approximately 30% of the jobs finishing tardy, using the FCFS sequencing rule. Again, the dynamic routing method outperformed (by 29.8%, 39.7%, and 28.4% in tardiness and by 26.4%, 40.7% and 23.1% in absolute lateness) the fixed routing method at 85%, 90% and 95% utilization.

It is interesting to note that the standard deviations under the dynamic routing method are sometimes greater. This is probably because the dynamic routing method reduces the workload in a high utilization cell by increasing the disruption in a low utilization cell.

4.2 Different Types of Demand Patterns

In the previous experiments each part was equally likely to be selected as the next order in the system. In this experiment the degrees of membership of the parts are sorted in descending order. The skewed-right demand pattern alters demand to favor high-fit parts, and the skewed-left demand pattern alters demand to favor low-fit parts. What is the result of having increased demand for high-fit parts or low-fit parts? Figure 6 shows the impact of the routing methods on mean flowtime, mean tardiness, and mean absolute lateness when the demand pattern changes to skewed left (low fit). The dynamic routing method improved flowtime (by 21.8%, 36.4%, 38.4%, 25.7%, and 14.4%), tardiness (by 15.5%, 36.9%, 41.4%, 29.0%, and 13.9%), and absolute lateness (by 1.2%, 27.7%, 35.3%, 27.2%, and 16.4%) at 75%, 80%, 85%, 90%, and 95% utilization. The performance measures for skewed right (high fit) pattern are shown in Figure 7. The high fit pattern deteriorates the advantages of the dynamic routing method. However, the dynamic routing method still improved flowtime (by 4.2%, 5.9%, and 16.9%), tardiness (by 4.7%, 26.0%, and 9.3%), and absolute lateness (by 4.2%, 5.9%, and 4.5%) at 85%, 90%, and 95% utilization. Not surprisingly, when the higher demand is for the high-fit parts, the performance measures are better.

It is interesting to note that compare to Figure 3, 4, and 5 the performance switching point is moving to the left (toward lower system utilization level) in Figure 6 with low fit demand pattern and to the right (toward higher system utilization) in Figure 7 with high fit demand pattern. This can be explained as follows. With high fit demand pattern, most of parts are highly fit to the FMC that are designed for them. Any intercell movement is most likely to increase disruption in an FMC. Not until the shop becomes busy (85% utilization or higher) can the dynamic routing method gain performance advantages by balancing workloads among FMCs. With low fit demand pattern, on the other hand, the general purpose machines in FMCs can easily become bottlenecks with many low fit (highly disruptive) parts. The dynamic routing method can, therefore, improves the system performance even at lower system utilization by releasing temporal bottleneck machines in FMCs.

5. SUMMARY AND FUTURE RESEARCH

In this research, we presented a dynamic routing method designed for the routing of part families among FMCs. The proposed dynamic routing method was compared with a traditional fixed routing method using three different performance criteria. The dynamic routing method performed much better than the fixed routing method on all three performance measures at high system utilization levels. However, when the cells were at low utilization, the fixed routing method performed better. The dynamic routing method showed better flowtime, tardiness, and absolute lateness over a varied set of distributions of part demand and machine breakdowns.

Despite the indication of advantages from the implementation of the dynamic routing method, further research is warranted. In this experiment, the performance switching point is occurred between 80% and 85% system utilization. It would be interesting to know how this point varies with the size of FMCs, the number of part families, or different dispatching rules. Knowing the behavior of the switching point will help shop managers to choose right routing methods. While this study examined dynamic routing among FMCs at the system level, future research should also examine the impact of the dynamic routing method within the FMCs at the cell level. It would be interesting to see the effect of combining dynamic routing among FMCs and within the FMCs, that is, both at the system and the cell levels.

The aim of the dynamic routing approach is to take full advantage of the inherent flexibility of an MCFMS. While the results reported here appear promising for systems with high utilization rates, additional studies will be required to assess the scope of MCFMS configurations that benefit from dynamic routing. Implementation of the dynamic routing procedure as presented here does require a general purpose machine in each cell of a company's MCFMS layout, but the calculations required in real-time for the routing decisions are very simple. Unlike most of dynamic routing methods that require to regenerate the entire set of operations including those unaffected by the change in conditions and demands. This is time consuming, and often results in response times unacceptable to the user.

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