ATTRIBUTE SELECTION FOR THE SCHEDULING OF FLEXIBLE MANUFACTURING SYSTEMS BASED ON FUZZY SET-THEORETIC APPROACH AND GENETIC ALGORITHM

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ABSTRACT

Assigning proper dispatching rules dynamically has been shown to enhance various performance measures for a flexible manufacturing system (FMS). To achieve this, real-time salient information of the system is extracted and then a rule's dispatching mechanism is built for the scheduling task. For a dynamic scheduled FMS, two critical issues dominate the performance; the first is the selection of system attributes and the second is the design of the dispatching mechanism. This paper aims to deal with the first issue.

A good attribute evaluation method should provide the information from which attribute are selected or removed. In this paper, a supervised attribute mining algorithm (SAMA), which is based on the fuzzy set-theoretic approach and genetic algorithm (GA), is proposed to execute this function. SAMA is able to rank attributes according to their relative importance. In the experiment, a FMS is conducted to demonstrate the validity of the proposed SAMA. The experimental results indicate that the attribute evaluation task and optimal attribute subset selection can be achieved by using the SAMA. Moreover, compared with using all system attributes without selection, performance of the FMS can be improved by using the optimal attributes as input of the scheduler.

Keywords: *Flexible manufacturing system, dynamic scheduling, attribute selection, fuzzy theory, genetic algorithm*

1. INTRODUCTION

An FMS combines the merits of an automated production/transfer line and the flexibility of a job shop. An FMS is able to manufacture a number of different parts on a variety of groups of machines and other stations, such as load/unload and input/output buffers, by an automated material handling system [1-4]. With the above benefits, an FMS has several significant advantages including the improvement of machine utilization, enhancement of the throughput, reduction of the number of work-in-process (WIP), mean flow time, the number of tardy parts, and the use of smaller batches.

Scheduling plays an important role in the production control in an FMS, which contains several real-time decisions, such as part type and machine selection [3]. Since Montazeri *et al*. [5] had concluded that dispatching rules have a great impact on various system performance criteria, researchers started to investigate the relationship between various system performance criteria and the assigned dispatching rules for FMSs. Several methods have been proposed over the last decade and can be divided into several categories, including simulation-based and scheduling with dispatching rules [6-7], artificial intelligence (AI) approaches [8-9], dynamic programming approaches [10-11], heuristic approaches [3, 12-13], pre-emptive method [14], and the hybrid approaches [15-16].

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To achieve high performance for an FMS, a good scheduling system should make a right decision at a right time according to system statuses. Although a number of scheduling approaches have been proposed, the selection of system statuses, i.e., the system attributes, were accomplished by taking trail-and-error or heuristic rules. However, a set of better attributes would achieve higher classification accuracy for the rules dispatching because the *attribute* and *dispatching rule* refer to the *feature* and the *class* in the pattern recognition domain, respectively. Therefore, performing an attribute selection mechanism to obtain a set of salient attributes for the scheduling can reduce the time of designing and achieve higher classification accuracy so that high system performance of FMSs is attained. This paper aims to achieve this goal.

Various useful classical statistical techniques to achieve feature evaluation have been described [17]. Several methods based on fuzzy set theory [18-21] have also been proposed. Fuzzy set theoretic approaches to feature selection are based on entropy and fuzziness index measures [20-21], fuzzy *c*-means [18], and ISODATA algorithms [19]. Other approaches for feature selection are based mainly on artificial neural networks [22-25] and hybrid methods [26-28]. These methods are classified as supervised or unsupervised based on whether the class information is known or not. For example, the methods proposed in [20-23,26,28] fall into the supervised category, whereas those in [19,24-25,27] are unsupervised.

The proposed SAMA combines some attempts: using the fuzzy set-theoretic approach and GA optimization under the supervised training. The underlying principle includes the development of a multi-dimensional fuzzy- entropy-based attribute evaluation index (FAEI) and optimization using GA with population solutions. SAMA can automatically provide useful information so that we can select optimal attribute subset from the original attribute set according to their *relative importance* in the attribute space.

The rest of this paper is organized as follows. Details of the proposed supervised attribute mining algorithm (SAMA) will be illustrated in Section 2. Section 3 will formulate the FMS model for the experiment, including the physical layout and the product order. Experimental results and some discussions will be given in Section 4. Finally, we have some conclusions in Section 5.

2. SUPERVISED ATTRIBUTE MINING ALGORITHM

This section will introduce the formulation of the proposed SAMA. It is noted that one dispatching rule forms one class. If there *n* system attribute candidates to be evaluated, a row data, called a pattern, is in *n*-dimensional attribute space.

2.1 Fuzzy entropy based attribute evaluation index

Suppose that there are l classes ($C_1, C_2, ..., C_k, ..., C_l$) to be classified, and each class has *p* patterns. The attribute space for representing a pattern is an *n* dimensional attribute space $F = (F_1, F_2, ..., F_n)$, in which the attribute components denote various kinds of features. The distance between a pattern $F_j \in C_k$ and its corresponding mean in class C_k is defined as the normalized Euclidean distance:

$$d_k(F_j) = \left[\sum_{i=1}^{n} \left(\frac{|F_{ij} - m_{ki}|}{\alpha_{ki}} \right)^2 \right]^{1/2}, \quad F \in C_k \tag{1}$$

where

$$m_{ki} = \frac{1}{p} \sum_{j=1}^{p} F_{ij} \tag{2}$$

and

$$\alpha_{ki} = N_1 \cdot \max_j |F_{ij} - m_{ki}|, \quad F_i \in C_k \tag{3}$$

In the above equations, m_{ki} denotes the mean of class C_k along the ith attribute axis, α_{ki} is a normalization factor, in which N_1 is a positive number so that the value of $d_k(F_j)$ would lie in the interval [0, 0.5], and *p* is the class size. We can use the multi-dimensional $semi-\pi$ membership function to compute the intraclass ambiguity with the fuzzy entropy [32]

$$H_k = \frac{1}{p \ln 2} \sum_{j=1}^{p} S_p(\mu_{semi-\pi}(d_k(F_j))), \quad F_j \in C_k \tag{4}$$

where $S_p(\bullet)$ is the Shannon function and is expressed as

$$S_p(\mu(x)) = -\mu(x) \ln \mu(x) - (1 - \mu(x)) \ln(1 - \mu(x)) \tag{5}$$

where the multi-dimensional $semi-\pi$ membership function is defined as

$$\mu_{semi-\pi}(x) = \begin{cases} 1 - 2x^2 & , if\ 0 \le x \le 0.5 \\ 0, \quad if\ x > 0.5\ and\ x < 0 \end{cases} \tag{6}$$

The value of the index H_k increases monotonically as the value of $d_k(F_j)$ increases monotonically in the interval [0, 0.5]. Hence, if most of the patterns are concentrated around the center, the value of the index H_k would then be low. In this case, the compactness of patterns $F_j \in C_k, j = 1,2,...., p$ is high. Compactness index H_k represents the intraclass ambiguity.

Let $m_{kk'i}$ be the center of classes C_k and $C_{k'}$ along the ith feature axis, $k \neq k'$, $k, k' = 1,2,...,l$

$$m_{kk'i} = \frac{1}{2p}\left[\sum_{j=1}^{p}(F_{ij})_k + \sum_{j=1}^{p}(F_{ij})_{k'}\right] \tag{7}$$

where patterns $(F_{ij})_k$,and $(F_{ij})_{k'}$ belong to class C_k and class $C_{k'}$ respectively. The normalized Euclidean distance between the pattern and center of the two classes C_k and $C_{k'}$ is defined as

$$d_{kk'}(F_j) = \left[\sum_{i=1}^{n}\left(\frac{\left|F_{ij} - m_{kk'i}\right|}{\alpha_{kk'i}}\right)^2\right]^{1/2}, \quad F_j \in C_k \cup C_{k'} \tag{8}$$

and

$$\alpha_{kk'i} = N_2 \cdot \max_j \left|F_{ij} - m_{kk'i}\right|, \quad F_j \in C_k \cup C_{k'} \tag{9}$$

where the factor $\alpha_{kk'i}$ is the normalization factor so that the $d_{kk'}(F_j)$ value would lie in the interval [0, 0.5] and N_2 is a positive real number. We can also obtain the membership value of the pattern $F \in C_k \cup C_{k'}$ to the center of these two classes using the multi-dimensional $semi - \pi$ membership function. Furthermore, the interclass ambiguity between the two classes can be obtained by computing the index of fuzziness (Kaufmann entropy) [33] for all patterns in the given two classes. Namely

$$\gamma_{kk'} = \frac{1}{p}\left[\begin{array}{l}\sum_{j=1}^{p}\mu_{(semi-\pi)\cap(\overline{semi-\pi})}(d_{kk'}(F_j^k)) + \\ \sum_{j=1}^{p}\mu_{(semi-\pi)\cap(\overline{semi-\pi})}(d_{kk'}(F_j^{k'}))\end{array}\right] \tag{10}$$

where $F_j^k \in C_k$ and $F_j^{k'} \in C_{k'}$. From the above equation, the Kaufmann entropy $\gamma_{kk'}$ has the minimum ($\gamma_{kk'} = 0$) as the $d_{kk'}(F)$ value equals zero, and $\gamma_{kk'}$ has the maximum ($\gamma_{kk'} = 1$) as the value of $d_{kk'}(F) = 0.5$. If most of the patterns $F \in C_k \cup C_{k'}$ are clustered around the center of the two classes, the value of $\gamma_{kk'}$ tends to zero. Hence, the $\gamma_{kk'}$ value decreases as the goodness of the features in discriminating between classes C_k and $C_{k'}$ decreases. The index of fuzziness $\gamma_{kk'}$ denotes the interclass ambiguity and is called the separation index in this paper.

Based on the compactness and separation indices mentioned above, SFM defines a fuzzy-entropy-based attribute evaluation index (FAEI):

$$FAEI = \sum_{k=1}^{l}\frac{H_k(F)}{\sum_{k \neq k'}\gamma_{kk'}(F)} \tag{11}$$

The term $H_k(F)/(\sum_{k\neq k'}\gamma_{kk'}(F))$ is close to the minimum as $H_k(F)$ tends to zero and $\sum_{k\neq k'}\gamma_{kk'}(F)$ tends toward the maximum. Conversely, this term has the maximum when $H_k(F)$ =1 and $\sum_{k\neq k'}\gamma_{kk'}(F)$ approaches zero. The FAEI index value decreases as the pattern *F* increases its membership value to its own one class, i.e., *F* increases its belongingness to only one class. In the meantime, *F* decreases its interclass ambiguity. The FAEI value increases as the pattern *F* decreases its belongingness to a specific class C_k . In the meantime, it increases the ambiguities toward other some classes for some $k' \neq k$. Hence, the attribute evaluation becomes a task of minimizing the FAEI index, i.e., one can find the optimal attribute space subset by minimizing the FAEI index. However, there are no arguments in the index by which the FAEI can be minimized. Namely, there is no information about the relative importance of each feature F_i in the *n*-dimensional feature space.

In our previous study [28], the relationship between relative importance of a feature and its weighted factor has been derived. By incorporating the weighting factors into normalized Euclidean distances, the weighted distances are

$$d_k(F_j, \varpi) = \left[\sum_{i=1}^{n}\left(\omega_i \cdot \frac{\left|F_{ij} - m_{ki}\right|}{\alpha_{ki}}\right)^2\right]^{1/2}, \quad F_j \in C_k \tag{12}$$

$$d_{kk'}(F_j, \varpi) = \left[\sum_{i=1}^{n}\left(\omega_i \cdot \frac{\left|F_{ij} - m_{kk'i}\right|}{\alpha_{kk'i}}\right)^2\right]^{1/2}, F_j \in C_k \cup C_{k'} \tag{13}$$

where ϖ is the weighting set, $\varpi = (\omega_1,..\omega_i,.....,\omega_n)$, $0 < \omega_i < 1$, $i = 1,2.....,n$. FAEI is now a function of the set ϖ . Namely, the class structure in the attribute space can be dynamically changed by setting different combinations of weighting sets. The worse the discriminability of the classes along the ith attribute axis, the lower the weighting factor ω_i , i.e., the lower the relative importance of feature F_i . Conversely, the better the discriminability of the classes along the ith attribute axis, the higher the value of the weighting factor ω_i , i.e., the higher the relative importance of attribute F_i . Thus, attribute mining becomes the task of minimizing the FAEI subject to the set ϖ .

2.2 Minimizing the FAEI via GA

The optimization task can be performed in several approaches such as nonlinear programming and simulated Annealing algorithm [29-30]. In this study, we use the genetic algorithm [31] to search the global optimal weighting set so that FAEI can be minimized, and the steps are as follows

Step 1: Prepare the training set. Determine the population size, encoding mechanism, selection reproduction procedure, crossover rate, and mutation rate

Step 2: Start with an initial population randomly (a set of strings or chromosomes).

Step 3: Evaluation of fitness (inverse of FAEI) of every string and selection of appropriate candidate strings to form the mating pool.

Step 4: Crossover and mutation.

Step 5: Repetition of steps 3 and 4 until the stopping criterion is reached. Namely, the cost of FAEI for all populations remains at a low value and no changes are observed.

3. FMS FORMULATION AND SIMULATION SETUP

The FMS used in this paper is a modification of the model presented in [5], and is shown in Fig. 1. The FMS model consists of three machine families (M1, M2, and M3), three load/unload machines, and a WIP buffer with enough capacity to prevent deadlock. The M1 and M2 machine families have two machines respectively, while the third family M3 has one machine only.

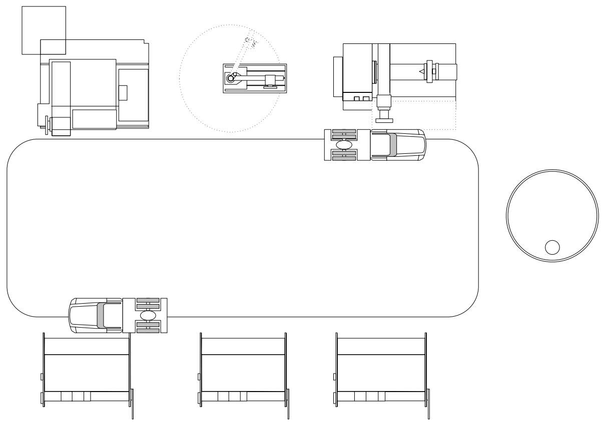

Figure1. FMS layout

Table 1. Part routing and processing times

Part ID	Part Routing	Processing Times (min.)
1	L,M2,L,M1,L,M2,L	3,11,10,20,3,14,3
2	L,M2,L,M1,L,M2,L,M1	3,10,10,24,3,10,3
3	L,M2,L,M1,L,M2,L	3,15,3,30,10,21,3
4	L,M2,L,M1,L,M2,L	3,12,3,53,10,33,3
5	L,M2,L,M1,L,M1,L,M2,L	8,16,5,25,5,22,10,24,8
6	L,M2,L,M1,L,M1,L,M1,L,M2,L	5,25,15,24,5,22,10,38,3,57,10
7	L,M2,L,M1,L,M1,L,M1,L,M2,L	5,28,15,27,5,25,10,40,3,35,10
8	L,M2,L,M1,L,M1,L,M1,L,M2,L	5,36,15,30,5,32,10,49,3,25,10
9	L,M2,L,M1,L,M1,L,M1,L,M2,L	5,45,15,42,5,34,10,80,3,23,10
10	L,M2,L,M1,L,M1,L,M1,L,M2,L	5,52,10,61,5,61,30,112,3,38,50
11	L,M3,L,M3,L,M2,L,M2,L	12,95,12,45,3,36,50,51,21

Table 2. Dispatching rules used in the scheduled FMS

Dispatching rule	Description
FIFO	Select the job according to the rule of first in first out
SPT	Select the job with the shortest processing time
SIO	Select the job with the shortest imminent operation time
SRPT	Select the job with the shortest remaining processing time
CR	Select the job with the minimum ratio between time now until due-date and its remaining processing time
DS	Select the job with minimum slack time
EDD	Select the job with the earliest due-date

Table 3. Attribute candidates to be evaluated for the scheduling of the FMS

Attribute	Description	Attribute	Description
Njob	Number of the jobs in the system	**MaRT**	The maximum remaining processing time of candidate jobs within the system
MeUM	The mean utilization of machines	**MeRT**	The mean remaining processing time of candidate jobs within the system
SdUM	The standard deviation of machine utilization	**SdRT**	The standard deviation of the remaining processing time of candidate jobs within the system
MeUL	The mean utilization of load machines	**MiST**	The minimum slack time of candidate jobs within the system
MiOT	The minimum imminent operation time of candidate jobs within the system	**MeST**	The mean slack time of candidate jobs within the system
MaOT	The maximum imminent operation time of candidate jobs within the system	**SdST**	The standard deviation of the slack time of candidate jobs within the system
MeOT	The mean imminent operation time of candidate jobs within the system	**MaTA**	The maximum tardiness of candidate jobs within the system
SdOT	The standard deviation of the imminent operation time of candidate jobs within the system	**MeTA**	The mean tardiness of candidate jobs within the system
MiPT	The minimum total processing time of candidate jobs within the system	**SdTA**	The standard deviation of the tardiness of candidate jobs within the system
MaPT	The maximum total processing time of candidate jobs within the system	**MeSO**	The mean sojourn time of candidate jobs within the system
MePT	The mean total processing time of candidate jobs within the system	**SdSO**	The standard deviation of the sojourn time of candidate jobs within the system
SdPT	The standard deviation of the total processing time of candidate jobs within the system	**MeTD**	The mean time now until due date of candidate jobs within the system
MiRT	The minimum remaining processing time of candidate jobs within the system	**SdTD**	The standard deviation of the time now until due date of candidate jobs within the system

Different part types have different processing routes. Each part has to be processed among the three families but with different sequences. Namely, each part type has its own processing route. The sequence of operations for each part is fixed, and the routes (process plans) of the eleven part types are listed in Table 1. In this table, the load and unload machines are denoted by *L*.

Several assumptions are as follows. Different jobs arrive randomly at the FMS with a constant time interval of 31 minutes and every job has its due date. The transportation time is considered to be negligible in this paper and each machine can only process a job at a time. Seven dispatching rules that have been used in the scheduling researches are selected in this paper and are listed in Table 2. Furthermore, three performance criteria are chosen and they are throughput (TP), mean flow time (MFT) and number of tardy parts (TD), respectively.

A scheduler seeks to identify important system attributes under various performance criteria. Therefore, all possible system attributes are exhaustively examined. Table 3 lists the 26 attribute candidates that will be examined in this paper. These attribute candidates are selected from the earlier researches [34-37]. This paper aims to apply the proposed SAMA to select salient attribute subset from a large number of attribute candidates.

4. RESULTS AND DISCUSSIONS

1) Training set preparation for the attribute selection

A training set is generated by executing a number of simulation runs under a specific performance criterion. Three training sets have to be prepared because three performance criteria are used. The simulation period for each run is 10,080 minutes composed of 7 multi-pass scheduling periods and the time interval of making a decision is 1440 minutes. A dispatching rule is assigned to the next scheduling period randomly at each decision point. It is noted that the first dispatching rule for the long run is set as the FIFO. Time between the arrivals of various jobs is set as 31 minutes. Three different part mix ratios are used (see Table 4) and each part ratio has 40 random seeds to generate 40 distinct job arrival sequences. Totally 120 job arrival sequences are generated.

By taking trail-and-error, a training instance is obtained which has the optimal performance through a large number of simulations under a specific part ratio and a specific job arrival sequence. A training instance supports seven training row data, each of which is a row vector of dimensionality 27. Dispatching rules are labeled from Class 1 to Class 7. Therefore, there are totally 840 training row data

Table 4. Defined part ratios in this study (%)

Part	Ratio 1	Ratio 2	Ratio 3
Lot 1	25	11	5
Lot 2	5	11	5
Lot 3	5	11	5
Lot 4	8	12	16
Lot 5	16	6	16
Lot 6	16	8	9
Lot 7	1	8	8
Lot 8	5	7	8
Lot 9	12	7	7
Lot 10	5	2.5	4
Lot 11	2	16.5	16

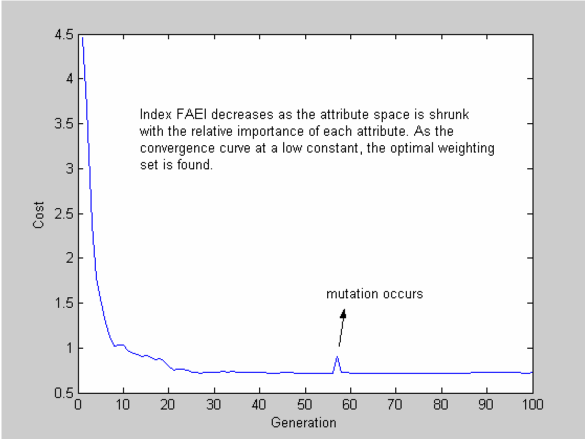

Figure 2. Minimizing FAEI via GA

obtained under a specific performance criterion. Namely, a training set is a dimension of 840 by 27. The simulation of the FMS is realized by the tool of eM-Plant v4.6.

2) *GA setting*

After deriving SAMA, the dynamically scheduled FMS is used to validate the algorithm. Also, the proposed SAMA is used to find the salient attribute subset from 27 candidates for the scheduling. Before performing GA to minimize the index *FAEI*, some genetic operations in GA search must be set first.

All weighting factors are randomized in [0,1] initially, and then encoded into binary 10-bit strings (chromosomes). Therefore, the resolution of a weighted factor is 1024 in [0,1] such that the relative importance can be obtained more precisely. The population size is set to 200, the mutation rate is set to 0.01%, and the crossover rate is set to 1.0. The roulette wheel selection is used to be the evolution operation. The fitness function is defined as the inverse of the index *FAEI*, and the cost of each generation is defined as the summation of all populations in the generation.

A genetic algorithm search with 50 generations is called a run. It is worth mentioning that the time of a run is less than two minute by using a personal computer with Pentium IV-2.66 GHz CPU. The off-line attribute evaluation process is coded with Matlab 5.3. This indicates that the attribute evaluation task can be accomplished in a very short time. Optimal weighting factors are determined when the convergence curve keeps at a constant during the evolution. A convergence curve of minimizing FAEI subject to weighting set via GA is shown in Fig. 2. In this case, the training set is obtained under the minimization of throughput performance that has been described in the training set preparation. The rank of an attribute is determined by its corresponding weighting factor, ω, i.e., the relative importance. The higher the rank is, the more important the attribute is.

3) *Evaluation via SAMA*

After setting parameters of GA, we perform SAMA three times to find the three optimal weighting sets of attributes since three performance criteria are used. The results are listed in Table 5. From Table 5, we can find some interesting results. As we had mentioned in the last section, the higher the weighting factor is, the more important of the attribute is. Therefore, we can rank these attributes according to their relative importance. For instance, five attributes, SdUM, MeUL, MeTA, MeRT and SdTA, are better attributes for all performance criteria because their corresponding weighting factors are high compared with other attributes. Another interesting result is that an attribute may be the best one for one performance criterion while it may be the poor attribute for the rest performance criteria. For instance, for performance TP, MiRT is the best attribute ($\omega = 0.8189$) while it shows inadequacies for classifying dispatching rules for both performance MFT ($\omega = 0.3054$) and TD ($\omega = 0.1260$). This indicates that salient attributes of each performance may not be the same.

It is necessary to determine a threshold such that those system attributes, whose weighting factors that are larger than the threshold, are chosen as salient attribute subset. In this study, we define the threshold as 0.6. The selected attributes for each performance criterion are listed in Table 6.

4) *Validity demonstration with classification accuracy*

After the attribute selection, we have to demonstrate the validity of the results. The relative importance of the attributes, obtained from SAMA, can be validated in two ways. The first is the scatter plots, which displays the patterns in 2D or 3D

Table 5. Optimal weighting factors of attributes resulted from SAMA among different performance criteria

Attribute	Optimal weighting factors ω_i TP	MFT	TD
Njob	0. 3529	0. 4488	0. 5407
MeUM	0. 5633	0. 6076	0. 6104
SdUM	0. 6652	0. 7700	0. 7034
MeUL	0. 6191	0. 6828	0. 6393
MiOT	0. 6072	0. 5367	0. 4903
MaOT	0. 4570	0. 4700	0. 4380
MeOT	0. 7220	0. 6046	0. 5667
SdOT	0. 5455	0. 4782	0. 4880
MiPT	0. 3632	0. 3288	0. 3112
MaPT	0. 3398	0. 2425	0. 3009
MePT	0. 5143	0. 4752	0. 5287
SdPT	0. 5159	0. 5149	0. 5275
MiRT	0. 8189	0. 3054	0. 1260
MaRT	0. 4237	0. 5568	0. 4765
MeRT	0. 6132	0. 6030	0. 6182
SdRT	0. 5450	0. 4216	0. 5401
MiST	0. 5561	0. 5418	0. 6231
MeST	0. 2536	0. 2726	0. 4044
SdST	0. 5613	0. 6081	0. 6037
MaTA	0. 5561	0. 5418	0. 6431
MeTA	0. 6489	0. 6114	0. 6101
SdTA	0. 7065	0. 6127	0. 7006
MeSO	0. 4771	0. 4815	0. 2154
SdSO	0. 5222	0. 3697	0. 3363
MeTD	0. 3731	0. 4561	0. 4316
SdTD	0. 4809	0. 4951	0. 4261

Table 6. Selected system attributes with threshold 0.6

Performance	Selected system attributes
TP	SdUM, MeUL, MiOT, MeOT, MiRT, MeRT, MeTA, SdTA
MFT	MeUM, SdUM, MeUL, MeOT, MeRT, SdST, MeTA, SdTA
TD	MeUM, SdUM, MeUL, MeRT, MiST, SdST, MaTA, MeTA, SdTA

attribute space, providing the visualization of pattern distribution, i.e., the structural description.

In this case, the scatter plots are not easy to obtain because the number of system attributes is so large that the number of scatter plots becomes comparatively much larger. Since there are 26 attribute candidates to be evaluated, $26!/(2!24!) = 325$ 2D scatter plots are needed at most. It is difficult to accomplish this task compared with displaying scatter plots of Iris data [28]. The second way is the usage of the classification result.

In order to demonstrate the validity of the ranking from the SAMA, the *k*-nearest neighbor (*K*-NN) algorithm is used as the classifier to acquire the classification rates for three sets of attributes. The first set contains all the 26 attribute candidates. The second set is the attribute subset obtained from the SAMA and the defined threshold (see Table 6). The third is the complement of the second set. Namely, the values of weighting factors of the attributes in the third set are smaller than those in the second set for every performance criterion. In order to avoid the existence of a tie, the *k* is set as an odd value, *k*=3. The classification results are listed in Table 7.

From the results, it is found for the second set that the *K*-NN classifier results in 74.34%, 76.32%, 75.98% for the seven classes defined in Table 2 under the three performance criteria TP, MFT, and TD, respectively. They are much higher than the results given by the first and the third sets. Obviously, the third set, in which the attributes have lower weighting factors, will encumber the classification rate when selecting all the attributes to classify the seven dispatching rules. According to classification results shown in Table 7, the selected attributes obtained from SAMA can indeed achieve higher classification accuracy. Also, the results obtained from the proposed SAMA demonstrate the validity of the ranking results.

It is worth mentioning that the classification rate can be enhanced by using many advanced classification techniques such as neural networks and fuzzy logic inference engine. However, the goal of this study is to provide an automatic solution to attribute selection for the scheduling of an FMS, which is able to select an optimal attribute subset from attribute candidates without taking trial-and-error. This can make the classifier design easier and can achieve higher classification rate. However, the *K*-NN classifier used here is just to acquire the classification rates that describe the pattern distribution in attribute space indirectly. The study of intelligent scheduler design will be the one of the critical issues for the scheduling of FMS in the future.

Table 7. Classification rates of using different attribute sets as inputs of *K*-NN classifier among different performance criterion (%)

	TP	MFT	TD
The first set (26 attributes, see Table 3)	57.60	61.34	64.56
The second set (selected attributes, see Table 6)	74.34	76.32	75.98
The third set (complement of the second set)	44.13	42.76	48.48

5. Conclusion

Selecting a set of proper system attributes as input of a scheduler is critical to the dispatching problem of the flexible manufacturing system (FMS).

This paper proposes a supervised attribute mining algorithm (SAMA), which is able to automatically select salient system attributes possessing the salient discriminative abilities for classifying dispatching rules. SAMA achieves this goal, according to simulation results under three different performance measures. Also, the selected attributes enhance the classification accuracy of rule dispatching for the FMS.

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基於模糊理論與基因演算法的彈性製造系統排程屬性選擇

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摘要

動態地給予一個彈性製造系統適合的派工法則可以增加產出、降低平均流程時間、及減少延遲工件等。爲了達到這個目的，即時的系統顯著資訊必須擷取，然後依據萃取出的資訊建立派工機制。兩個重要的議題主導著動態排程彈性製造系統的性能；其一是如何選取有用的系統屬性，另外就是派工機制的設計。本論文目標在於解決第一個議題。

一個好的屬性評估方法必須要提供哪些屬性該選擇，哪些該捨去的資訊。因此，在本文中提出了一個以模糊理論及基因演算法爲基礎的監督式屬性探勘演算法(supervised attribute mining algorithm, SAMA)來處理上述的問題。此演算法可以依照各屬性彼此之間關聯程度的重要性來給予排序。本文實驗利用模擬軟體建立了一個彈性製造系統來驗證此演算法的有效性。實驗結果指出 SAMA 可以達到屬性評估跟最佳化的屬性子集合選取等目的。更進一步，利用所得出的最佳化屬性子集合與未經過 SAMA 處理的系統全部屬性來做比較。最後，結果顯示經由 SAMA 選擇的屬性當成排程器的輸入可以提升彈性製造系統的性能。

關鍵詞：彈性製造系統，動態排程，屬性選擇，模糊理論，基因演算法

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