생산자료기반 부품-기계행렬을 이용한 부품-기계 그룹핑 : 인공신경망 접근법 - Part 2

Part-Machine Grouping Using Production Data-based Part-Machine Incidence Matrix: Neural Network Approach - Part 2

원유경

전주대학교 경상대학 경영학부(wonyk@jj.ac.kr)

Abstract

This study deals with the part-machine grouping (PMG) that considers realistic manufacturing factors, such as the machine duplication, operation sequences with multiple visits to the same machine, and production volumes of parts. Basically, this study is an extension of Won(2006) that has adopted fuzzy ART neural network to group parts and machines. The proposed fuzzy ART neural network algorithm is implemented with an ancillary procedure to enhance the block diagonal solution by rearranging the order of input presentation. Computational experiments applied to large-size PMG data sets with a psuedo-replicated clustering procedure show effectiveness of the proposed approach.

1. Introduction

Basically, this study is an extension of Won (2006) that has adopted fuzzy ART neural network to group parts and machines for the design of cellular manufacturing system.

Won(2006) proposed two-phase methodology to solve the PMG problem that considers realistic manufacturing factors, such as the operation sequences with multiple visits to the same machine and production volumes of parts. Based on the application of production data-based part-machine incidence matrix(PMIM) (Won & Lee 2001), phase 1 (clustering phase) of the two-phase methodology has attempted to find part families and machines cells quickly with Fuzzy ART neural network algorithm. Phase 2 (reassignment phase) has sought to find the best proper block diagonal solution by reassigning exceptional parts and machines with the purpose of minimizing inter-cell part moves and maximizing within-cell machine utilization. The two-phase methodology has been justified on large-size data sets generated with a psuedo-replicated clustering procedure which is a modification over conventional replicated clustering procedure.

In this study some extension will be conducted over the existing two-phase methodology. First, phase 1 will be extended with an ancillary procedure to enhance the block diagonal solution by rearranging the order of input presentation. Second, the constraint of machine duplication will be incorporated into the existing procedure of phase 2. Such an extension can lead to improvement of the applicability of the existing two-phase methodology since real manufacturing shops usually have multiple, functionally identical machines for a given type of machine(Mini *et al.* 1990). The proposed methodology will be justified on large-size data sets generated with the psuedo-replicated clustering procedure.

2.Methodology

2.1 Extended procedure of phase 1

The extended procedure of phase 1 re-adopts the type I production data-based PMIM in Won and Lee(2001) and the input representation scheme into Fuzzy ART neural network proposed in Won(2006). For the explanation of terminologies, readers are referred to Won(2006).

In our extended procedure of phase 1, we extend Chen and Cheng's rearrangement algorithm (1995) applied for the binary PMIM-based PMG problem into the rearrangement procedure applied for the production data-based PMG problem. The decay of exemplar template occurs so often when the fuzzy ART algorithm is applied to the PMG problem. The objective of extension of existing procedure of phase 1 is to quickly bring the most similar parts together.

Chen and Cheng's rearrangement algorithm identifies the exceptional machine (row) vectors and rearranges the machine vectors with less "1"s outside in descending order of the number of "1"s in the machine/part cluster. Our modified part order-rearrangement procedure starting with incumbent solution of part families is applied to the parts of each part family. Since our modified part order-rearrangement procedure is applied in each part family-base not the whole part-base, it can lead to significant saving of computational efforts in sorting the part vectors. The part-order rearrangement procedure proceeds as follows:

Part order-rearrangement procedure

Step 0 : Find the order of part vectors from the incumbent solution of part families obtained by applying the fuzzy ART algorithm and their machine cells obtained by applying the machine-assignment rule.

Step 1 : Identify the exceptional part vectors and set them aside.

Step 2 : For each part family, rearrange the part vectors with less flows outside in descending order of flows in the part/machine cluster. In the case of a tie, the part with more portions of operations within the part/machine cluster is presented first. In the case of a tie again, the part with the minimum flows outside the part/machine cluster is presented first.

Step 3 : Present the exceptional part vectors that were set aside in step 1.

2.2 Extended procedure of phase 2

The objective of the extended procedure of phase 2 is to find the cell configuration minimizing the sum of machine duplication if exceptional machines have extra identical machines.

An exceptional machine with extra identical machines available is duplicated to its next most preferred cell except its parent cell so as to minimize inter-cell part moves. Ties are broken by duplicating exceptional machine to the cell with the most portions of operations for parts so as to maximize within-cell machine utilization. The machine duplication rule is stated as follows:

Machine-duplication rule

- For each exceptional machine with extra identical machines available, find its next most preferred cell except its parent cell and duplicate it to that cell.
- If ties occur, select the machine cell which processes the most portions of operations for parts.
- In the case of a tie again, select the smallest machine cell.

2.3 Extended two-phase procedure

With the part-order rearrangement procedure and the machine duplication rule, the extended two-phase procedure is described as follows:

Clustering stage:

Step 0 : Set the iteration number $k=0$ and prepare for the input vectors.

Step 1 : For the specfied vigilance threshold ρ, choice parameter α and learning parameter β, apply Fuzzy ART algorithm to cluster parts into families.

Step 2 : Assign machines to their most appropriate cells.

Step 3 : Find exceptional parts and use part order-rearrangement procedure to rearrange them.

Step 4 : If $k \leq$ the predetermined target number of iteration, set $k=k+1$ and go to Step 1. Otherwise, go to Step 5.

Enhancement stage:

Step 5 : Apply the weighted maximum density rule to reassign improperly assigned parts and machines to their most appropriate part families and machine cells.

Step 6 : Duplicate identical machines with machine duplication rule.

Step 7 : If stopping condition is satisfied, stop. Otherwise, go to Step 5 and repeat.

3. Experimental results

3.1 Experiments with small-size problem

The proposed algorithm has been applied to the data set in Gupta and Seifoddini (1990) with 43 part types and 16 machine types. Since the authors do not provide the data on replicate machines, however, we adopt the information of replicate machines provided in Rao and Gu (1995) as follows:

- Machine type 6 : four
- Machine type 8 : three
- Machine type 11 : two.

In the experiment with this data set, the fuzzy ART neural network with $\alpha=0.5$ and $\beta=0.1$ is applied and the target number of iteration for phase 1 is set at 2. To evaluate the performance of the block diagonal solution, the weighted grouping capability index (WGCI) in Won(2006) has been re-adopted.

On this problem, Rao and Gu's algorithm (1995) requires six extra machines to be duplicated, whereas our extended two-phase procedure requires five extra machines to be duplicated under the identical number of clusters with the value of WGCI equal to 95.93%.

3.2 Experiments with large-size problems

To test the applicability of the proposed two-phase procedure on large-size data set, the data set used in the previous subsection has been expanded with the psuedo-replicated clustering procedure in Won(2006) with various expansion levels. In our experiments, the expansion levels equal to 2, 3, 4, and 5 have been applied. The target value of WGCI revealing the robustness and recoverability of the proposed algorithm to expanded problems is set at 95.93% under the configuration of clusters not less than 8, 12, 16, and 20, respectively, which are the minumum qualification numbers of clusters for each expansion level and the extra duplicated machines not more than 10, 15, 20, and 25, respectively, for each expansion level, For each expansion level, 30 problems have been generated and the order of part input vector has been randomly scrambled.

The extended two-phase procedure has been written in C++ object-oriented programming language and implemented on an IBM compatible Pentium III PC with 1 GHrz. The experimental results are reported in tables 6. The clustering stage of phase 1 has been implemented by lowering the vigilance threshold ρ by 0.01 from 0.95 to 0.70 for each expanded problem instance.

<Table 1> Experimental results

	Expansion level											
	2			3			4			5		
Problem No.	ρ	WGCI	NDM*	ρ	WGCI	NDM	ρ	WGCI	NDM	ρ	WGCI	NDM
1	0.87	95.43	10	0.74	90.89	15	0.83	91.08	20	0.72	94.68	25
2	0.73	92.75	10	0.81	95.60	15	0.79	93.58	20	0.90	93.88	23
3	0.87	95.37	10	0.79	94.78	14	0.82	91.58	20	0.74	91.46	24
4	0.77	94.45	10	0.84	93.28	15	0.88	93.23	20	0.78	90.72	25
5	0.77	96.49	10	0.72	95.88	15	0.84	92.84	20	0.83	91.19	25
6	0.75	95.23	10	0.76	96.06	15	0.83	91.52	20	0.77	92.21	24
7	0.80	96.91	10	0.72	95.21	15	0.79	92.54	19	0.80	95.88	25
8	0.78	96.08	9	0.78	92.43	15	0.74	93.95	20	0.77	91.68	25
9	0.78	94.14	10	0.88	93.91	15	0.77	92.56	20	0.78	93.48	24
10	0.70	94.35	10	0.71	93.80	14	0.73	94.34	18	0.87	92.42	25
11	0.85	96.11	10	0.79	94.91	15	0.75	96.89	20	0.74	93.73	24
12	0.80	95.05	10	0.91	93.32	15	0.84	94.80	19	0.76	95.88	25
13	0.77	95.18	10	0.80	92.82	14	0.71	93.44	20	0.76	91.73	25
14	0.76	96.51	10	0.70	93.99	14	0.85	90.48	20	0.80	92.70	25
15	0.81	92.37	10	0.80	94.45	15	0.82	92.96	20	0.82	93.79	25
16	0.88	94.91	10	0.85	93.26	15	0.81	91.98	19	0.91	93.15	25
17	0.78	95.45	10	0.77	93.82	15	0.72	93.59	19	0.84	95.35	24
18	0.82	95.82	10	0.85	94.07	15	0.77	94.59	20	0.79	94.31	25
19	0.90	93.91	10	0.80	93.09	16	0.88	95.03	20	0.82	93.61	25
20	0.88	91.72	9	0.84	93.42	15	0.73	90.44	20	0.85	92.82	24
21	0.82	95.78	10	0.84	92.35	14	0.83	91.94	20	0.86	92.82	24
22	0.71	93.12	10	0.72	94.17	14	0.85	95.94	20	0.71	91.98	25
23	0.73	92.31	10	0.86	93.85	15	0.89	91.07	20	0.85	93.03	25
24	0.81	93.40	10	0.74	91.98	15	0.86	93.08	20	0.75	93.47	24
25	0.74	95.16	10	0.74	96.41	15	0.92	92.38	20	0.84	91.66	24
26	0.89	94.54	10	0.79	94.24	15	0.83	90.98	20	0.78	93.47	24
27	0.79	94.73	10	0.82	95.51	15	0.78	92.75	20	0.79	92.21	25
28	0.95	95.67	10	0.83	94.90	15	0.82	91.01	20	0.70	90.45	22
29	0.90	93.43	10	0.90	92.34	14	0.76	94.74	20	0.81	95.10	24
30	0.91	94.13	10	0.84	95.22	13	0.89	95.88	18	0.75	91.08	24
Average		94.72	9.9		94.00	14.5		93.05	19.7		92.96	24.4

<Table 1> shows the experimental results. It *can easily be noticed from <table 1> that* as the data expansion level increases the average value of WGCI tends to decrease slightly. But the average values of WGCI at the expansion levels of 4 and 5 do not show significant gap. Decreasing values of WGCI occur at the expense of slightly more blocks than the minimum qualification number of blocks and slightly less extra duplicated machines than the maximum qualification number of extra ones. For example, at the expansion level of 5 where the average experimental value of WGCI is lowest, the extended two-phase procedure tends to produce the solution with lower WGCI than the reference solution before expansion within the range of 3% on the average.

4. Concluding remarks

In this study, an extended two-phase procedure over Won(2006) has been developed to solve the PMG problem with multiple, functionally identical machines for each type of machines.

To enhance the solution quality from the application of fuzzy ART algorithm in phase 1, *an ancillary procedure to enhance the block* diagonal solution by rearranging the order of input presentation has been added to the previous stage in Won(2006). Extended phase 2 seeks to find the best proper block diagonal solution by reassigning exceptional parts and machines and duplicating multiple identical machines to cells with the purpose of minimizing inter-cell part moves and maximizing within-cell machine utilization.

The experimental results with large-size data sets shows the robustness and recoverability of the proposed procedure.

References

Chen, S.J., and Cheng, C.S. (1995), A new neural network-based cell formation algorithm in cellular manufacturing, *International Journal of Production Research*, **33**(2), 293-318.

Gupta, T. and Seifoddini, H. (1990), Production data based similarity coefficient for machine-part grouping decisions in the design of a cellular manufacturing system. *International Journal of Production Research*, **28**(7), 1247-1269.

Minis, I., Harhalakis, G.., and Jajodia, S. (1990), Manufacturing cell formation with multiple, functionally identical machines, *Manufacturing Review*, 1990, **3**(4), 252-261.

Rao, H. A. and Gu, P. (1995), A multi-constraint neural network for the pragmatic design of cellular manufacturing systems. *International Journal of Production Research*, **33**(4), 1049-1070.

Won, Y. (2006), Part-machine grouping using production data-based part-machine incidence matrix: neural network approach. Proceedings of KIIE/KORM 2006 Joint Conference.

Won, Y., and Lee, K.C. (2001), Group technology cell formation considering operation sequences and production volumes. *International Journal of Production Research*, **39**(13), 2755-2768.