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A heuristic algorithm for forming machine cells and part families in group technology

그룹 테크놀러지에서의 기계 및 부품군을 형성하기 위한 발견적 해법

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Abstract

A similarity coefficient based algorithm is proposed to solve the machine cells and part families formation problem in group technology. Similarity coefficients are newly designed from the machine-part incidence matrix. Machine cells are formed using a recurrent neural network in which the similarity coefficients are used as connection weights between processing units. Then parts are assigned to complete the cell composition. The proposed algorithm is applied to 30 different kinds of problems appeared in the literature. The results are compared to those by the GRAFICS algorithm in terms of the grouping efficiency and efficacy.

1. Introduction

Group technology(GT) is a philosophical concept which takes full advantages of similarity of items which are to be classified and processed. When GT is applied in the area of manufacturing, it takes the form of cellular manufacturing(CM) in which machines, tools and parts to be processed are grouped into cells according to the similarities of design features or production processes. Among various benefits from CM, reduced number of set-ups, reduced work-in-process inventories and reduced material handling cost are critical ones. For the successful implementation of CM, identification of relatively independent manufacturing cells is necessary in the design phase of CM system. Since Burbidge's[1] pioneering

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work on the production flow analysis, numerous methods for the machine cells and part families formation have been developed. Extensive survey and classification of grouping methods can be found in Chu[2], Cheng[3] and Offodile *et al.*[4]. One of the categories of classification is the similarity coefficient based method in which grouping procedure starts with the derivation of similarity coefficients from the machine-part incidence matrix. Based on the similarity coefficients, either an analytical method or a heuristic method for grouping is presented. McAuley[5], Carrie[6], Seifoddini and Wolfe[7] and Seifoddini[8] used linkage clustering, where the strength of linkage between machines or machine cells are calculated and then machines or machine cells are put together to form a larger machine cell. Rajagopalan and Batra[9] applied graph partitioning approach where the resulting subgraphs are taken as machine cells. Kusiak[10] formulated an integer programming model in which the objective is to maximize the sum of similarity coefficients of part pairs in same families. Srinivasan et al.[11] solved the assignment problem using the similarity coefficients matrix as the cost matrix to obtain machine cells and part families. Srinivasan and Narendran[12] modified the previous one by including repetitive column and row clustering procedure in the algorithm which they named GRAFICS-grouping using assignment method for initial cluster seeds. Srinivasan[13] used the minimum spanning tree to obtain clustering seeds from which part clustering and machine clustering followed.

In the other part of the world, many neural network models have been proposed to solve optimization problems and engineering problems[14]. Hopfield[15] suggested a neural network based approach for solving optimization problems using a fully connected recurrent network of processing units *i.e.*, neurons. The objective function and constraints of the optimization problem are mapped into a quadratic energy function of the network which is to be minimized through the evolution of the network. With respect to machine cells and part families formation problems, Moon[16, 17] suggested a grouping method based on interactive activation and competition network which consists of three pools of processing units, one each for parts, machines and part instances. Moon and Chi[18] extended the grouping method so that the sequence of part processing, production lot sizes of parts and multiple processing routes can be included for consideration. Kao and Moon[19] used a three layered feedforward neural network to form part families from a part pool where each part is tagged with binary and chain type classification code. Kaparthi and Suresh[20] used adaptive resonance theory 1(ART1) neural network[21, 22] in which clusters are found in an unsupervised mode. Later, Kaparthi, Suresh and Cerveny[23] improved the previous method by reducing loss of information during the execution of clustering algorithm. Suresh and Kapar-

thi[24] presented a cell formation method using fuzzy ART neural model[25] whose performance was compared to some existing methods including previous ART1 based method. Chu [26] used competitive learning algorithm to form the machine cells and part families where the number of cells to be formed was predetermined. Machine cells and part families were formed in separate networks and combined into a grouping solution. Chakraborty and Roy[27] reported a part-family classification method utilizing two different neural networks, self organizing feature map and backpropagation network. Venugopal and Narendran[28] compared neural network based cellformation methods including competitive learning model, ART model and self organizing feature map model.

In this paper, we propose another way of extracting similarity coefficient between machines from the machine-part incidence matrix. And then based on the recurrent neural network model[15] whose energy function is built upon the proposed similarity coefficients an algorithm for machine cell formation problem is presented. Parts are assigned to the cells to complete the cell composition. Grouping effectiveness of the proposed algorithm is compared to GRAFICS in terms of the grouping efficiency[29] and grouping efficacy[30]. The comparison is made via 30 different kinds of problems which appeared in the literature.

2. Similarity coefficients for machine cell formation

Let M be the number of machines to be grouped, N the number of parts to be processed on these machines and $A = \{a_{ip}\}(i = 1, 2, \cdots, M, p = 1, 2, \cdots, N)$ be the machine-part incidence matrix where $a_{ip} = 1$ if part p is processed on machine i, otherwise it is 0. Also let s_{ij} be the similarity coefficient between machine i and j.

Utilizing the similarity coefficients between machines, the machine cell formation problem can be formulated as follows

$$\text{Maximize} \sum_{k=1}^{M}\sum_{i=1}^{M}\sum_{j=1}^{M} s_{ij}X_{ik}X_{jk} \tag{1}$$

$$\text{subjects to} \sum_{k=1}^{M} X_{ik} = 1 \text{ for } i = 1, 2, ..., M \tag{2}$$

$$X_{ik} \in \{0, 1\} \text{ for } i \text{ and } k = 1, 2, ..., M \tag{3}$$

where $X_{ik} = 1$ if machine i belongs to the machine cell k, otherwise $X_{ik} = 0$.

By maximizing the sum of similarity coefficients of all machine pairs in the same cells, machine pairs with large positive value of s_{ij} will be put into the same cell. Compared to the objective function in the p-median model [9], the objective function (1) seems more reasonable because every machine pair in the same cell contributes to the objective function. Constraints (2) in the above model ensure that every machine will find its cell to be in. Instead of prescribing the number of machine cells to be formed, we let the grouping

algorithm determine it naturally.

Anderberg[31] listed various similarity measures for clustering binary data of the incidence matrix, yet the list is not final. From the incidence matrix A, let c_{ij} be the number of parts processed by both machine i and machine j and d_{ij} the number of parts processed by either machine i or j, not both. Using c_{ij} and d_{ij}, various similarity coefficients have been suggested[2, 4]. The well-known Jaccard's measure[5, 6] and Hamming's distance[10] are examples. Recognizing some drawbacks of these similarity coefficients, Seifoddini and Hsu [32] suggested a weighted similarity coefficient to overcome improper machine assignment. In the weighted similarity coefficients, c_{ij} and d_{ij} are weighted part by part.

Observing the objective function (1), the similarity coefficients should not be either all positive or all negative. Both cases will lead to extreme grouping solutions such as a solution of M singleton machine cells or a solution of single machine cell with M machines in it. In this regard, we propose the following similarity coefficients to be used in cell formation where α is a weighting factor.

$$s_{ij} = (c_{ij} - \alpha d_{ij}) / \max_{i,j} |c_{ij} - \alpha d_{ij}|$$

$$\text{for } i, j = 1, 2, ..., M \text{ and } i \neq j,$$

$$s_{ij} = 0 \quad \text{for } i, j = 1, 2, ..., M \text{ and } i = j. \qquad (4)$$

These similarity coefficients will lie in [-1, 1] due to the common denominator scale factor, $\max_{i,j} |c_{ij} - \alpha d_{ij}|$. If the similarity coefficient of a pair of machines is positive, the pair is encouraged to be in the same cell. Otherwise, it is better not to be in the same cell. The value of the weighting factor can be selected through some preliminary experiments. As a starting point, we suggest to use $\alpha = R$ where $R = C/D$, $C = \frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M} c_{ij}$ and $D = \frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M} d_{ij}$. With $\alpha = R$, $\sum_{i=1}^{M}\sum_{j=1}^{M} s_{ij} = 0$ and similarity coefficients distribute around zero. As α grows bigger, the value of similarity coefficient decreases to -1 and the number of machine cells formed tends to increase. By setting α to be some multiple of R, the effect of α on grouping solutions will be examined later through numerical experiments.

3. Cell formation algorithm based on a recurrent neural network

Hopfield[15] used a fully connected recurrent network of processing units to solve optimization problems. In discrete version of his model, each processing unit receives inputs from other processing units and an external source, which are weighted using connection weights between processing units and summed up to be compared to a threshold value. If the weighted sum of inputs exceeds the threshold, the processing unit will be firing *i.e.* the output of the processing unit becomes 1. Otherwise, the processing unit will not be firing and its output becomes 0. These binary output values of

processing units tell us the current state of network and they are put back into all processing units to be used as inputs in the following step, so the network is recurrent. This process repeats until the state of network is stabilized. A recurrent neural network can be designed and used to solve an optimization problem. The decision variables in the optimization problem are mapped into the output variables of the processing units. The objective function and constraints are put together into a quadratic energy function, E, representing the energy level of the network. From E, the connection weights for all pairs of processing units will be derived. If the matrix of connection weights is symmetric with zero diagonal elements, it has been shown that the network always converge to a stable state which corresponds to a local minimum point of E by Cohen and Grossberg[33]. The solution of the optimization problem can be retrieved from the output variables of processing units at any points of time during the network evolution.

The machine grouping problem in the previous section can be modeled as a recurrent neural network with M^2 processing units. Each decision variable X_{ik} is mapped onto the output variable V_{ik} of processing unit (i, k) where i and $k = 1, 2, ..., M$. $V_{ik} = 1$ if machine i belongs to cell k, otherwise $V_{ik} = 0$. The objective function and constraints are converted into the following energy function, E

$$E = \frac{B}{2}\sum_{i=1}^{M}\sum_{k=1}^{M}V_{ik}(1 - V_{ik}) + \frac{C}{2}\sum_{i=1}^{M}\left[\sum_{k=1}^{M}V_{ik} - 1\right]^2 - \frac{D}{2}\sum_{k=1}^{M}\sum_{i=1}^{M}\sum_{j=1}^{M}s_{ij}V_{ik}V_{jk} \quad (5)$$

where B, C, and D are weighting factors. The first two terms are for the constraints (2) and (3) in the optimization problem. These terms will vanish to zeros if the local point of E corresponds to a feasible solution of the optimization problem. The objective function, (1), appears in the third term of equation (5). The network will evolve from its initial state toward an equilibrium state which corresponds to a local minimum of the energy function E. Quite

often, local points are invalid solutions to the original optimization problem violating the restriction that each machine must belong to one and only one machine cell. To avoid this difficulty, we use the maximum neural network [34]. A cluster of M^2 processing units can be divided into M clusters of M processing units where each cluster is a potential machine cell and i th processing unit in each cluster indicates which cell machine i will belong to. Among M processing units for machine i, one and only one processing unit will be firing as follows

$$V_{ik} = 1 \quad \text{if } U_{ik} = \text{maximum } \{U_{i1}, U_{i2}, \cdots, U_{iM}\},$$
$$V_{ik} = 0 \quad \text{otherwise.} \quad (6)$$

where U_{ik} denotes the sum of weighted inputs to the i th processing unit in k th cluster.

In this way, every machine will find its one and only one cluster to be in. Coupled with the fact that V_{ik}'s are binary variables, equation (6) allows the energy function E to change into the following

$$E = -\frac{1}{2}\sum_{k=1}^{M}\sum_{i=1}^{M}\sum_{j=1}^{M} s_{ij}V_{ik}V_{jk} \tag{7}$$

The input to the processing unit (i, k) is updated by the following equation

$$\Delta U_{ik} = \sum_{j=1}^{M} s_{ij}V_{jk} + \varepsilon \tag{8}$$

where ε is a noise term hopefully preventing the network from settling down to a bad local minimum abruptly. From equation (8), we know that processing units receive excitatory or inhibitory signals from other processing units in the same cluster. If the connection weight *i.e.* similarity coefficient is positive, the signal will be excitatory. Otherwise, it will be inhibitory. A machine pair with large positive similarity coefficient is likely to have their processing units fire simultaneously in one cluster and be silent in all other clusters. A machine pair with large negative similarity coefficient is likely to have their processing units fire in two different clusters.

Once machine cells are formed, parts are assigned to the cells so that the number of exceptional elements that will appear in grouping solution to be minimized. If there are ties, part will be assigned to a cell with the least number of in-cell blanks. The proposed algorithm for forming machine cells and part families are described stepwise in the following.

1. Set $t = 0$.

2. Random numbers from the uniform distribution U(-0.5, 0.5) are assigned to the initial values of $U_{ik}(t)$ for all i and k.

3. Evaluate $V_{ik}(t)$ using equation (6). If the network is at an equilibrium state, go to step 6. Otherwise, proceed to the next step.

4. Calculate the incremental change of the input, $\Delta U_{ik}(t)$ for all i and k where

$$\Delta U_{ik}(t) = \sum_{j=1}^{M} s_{ij}V_{jk}(t) + \varepsilon(t). \tag{9}$$

$\varepsilon(t)$ is assumed to follow normal distribution $N\left(0, \frac{\tau}{\log(2+t)}\right)$. where τ is called the temperature parameter.

5. Calculate $U_{ik}(t+1)$ for all i and k as follows

$$U_{ik}(t+1) = U_{ik}(t) + \Delta U_{ik}(t) \tag{10}$$

Return to step 3.

6. (Assignment of parts) Given the machine cells $C_1, C_2, \cdots, C_K$, where K is the number of machine cells, the remaining problem is to find the corresponding part families $F_1, F_2, \cdots, F_K$. For part $p(p = 1, 2, \cdots, N)$, compute the followings;

$EX_k(p)$; the number of exceptional elements when processing of part p is confined to machine cell k.

$BN_k(p)$; the number of in-cell blanks when processing of part p is confined to machine

cell k.

Assign part p to the family k with the minimum EX-value. If two or more $EX_k(p)$ are tied for the minimum, choose the family with the minimum BN-value among them. In the case of tie in BN-values, choose a family arbitrarily.

4. Numerical example

To illustrate the proposed algorithm, an example problem with five machines and seven parts in King and Nakornchai[35] is solved. The machine-part incidence matrix of the problem is shown in Table 1a.

By definition, c_{ij}'s(d_{ij}'s) and similarity coefficients are obtained and listed in Table 1b and 1c. For example, we calculate s_{12} as follows;

From Figure 2b, we have $c_{12} = 0$, $d_{12} = 6$, $C = 11$, $D = 42$ and $R = 0.2619$. By setting $\alpha =$ 1 multiple of $R = 0.2619$, we have $\max_{i,j} |c_{ij} - \alpha d_{ij}| = 2.739$. So, $s_{12} = \frac{0 - (0.2619)(6)}{2.739} = -0.574$.

To see the iterative improvement of machine cell composition along with evolution of the network, computational results in each iteration are shown in Table 2. Also included in the table are the output variables, V_{ik}'s, intermediate machine cell composition retrieved from V_{ik}'s and the values of energy function, E. Value of E decreases until a stable point is reached. The machine cell forming procedure stops at the 4th iteration at which we have an identical result as in the 3rd iteration. At step 6, parts are assigned to machine cells. Table

Table 1. Incidence matrix, $c_i(d_{ij})$ values and simlarety coefficient matrix.

	Parts						
	1	2	3	4	5	6	7
1	0	1	0	1	1	1	0
2	1	0	1	0	0	0	0
3	1	0	1	0	0	1	1
4	0	1	0	1	0	1	0
5	1	0	0	0	1	0	1

Table 1a. Incidence matrix.

	Machines				
	1	2	3	4	5
1	-	0(6)	1(6)	3(1)	1(5)
2		-	2(2)	0(5)	1(3)
3			-	1(5)	2(3)
4				-	0(6)
5					-

C=11, D=42 and R=0.2619

Table 1b. c_{ij}'s(d_{ij}'s).

	Machines				
	1	2	3	4	5
1	0.0	-0.574	-0.209	1.000	-0.113
2	-0.574	0.0	0.539	-0.478	0.078
3	-0.209	0.539	0.0	-0.113	0.443
4	1.000	-0.478	-0.113	0.0	-0.574
5	-0.113	0.078	0.443	-0.574	0.0

average=0.000 and variance=0.245

Table 1c. Similarity coefficient matrix.

Table 2. Machine cell formation

No. of Iteration	V_{ik} values	Machine cells	E value
1	0 0 1 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 1 0 0 0 1 0	{1} {2,4} {3,5}	0.035
2	0 0 1 0 0 0 0 0 1 0 0 0 0 0 1 0 0 1 0 0 0 0 0 1 0	{1,4} {2,5} {3}	-1.078
3	0 0 1 0 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 0 0 0 1 0	{1,4} {2,3,5}	-2.060
4	0 0 1 0 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 0 0 0 1 0	{1,4} {2,3,5}	-2.060

Table 3. Grouping solution and its block-diagonal form.

K	Machines	Parts
1	{1,4}	{2,4,5,6}
2	{2,3,5}	{1,3,7}

Table 3a.

	2	4	5	6	1	3	7
1	1	1	1	1	0	0	0
4	1	1	0	1	0	0	0
2	0	0	0	0	1	1	0
3	0	0	0	1	1	1	1
5	0	0	1	0	1	0	1

Table 3b.

3 shows the grouping solution in table form 3a and block-diagonal form 3b. We note that the solution has two machine cells, *i.e.* $C_1 = \{1, 4\}$, $C_2 = \{2, 3, 5\}$ and contains 2 exceptional elements.

5. Computational experience

The performance of the proposed is examined by solving 30 different problems from various literature. To use the proposed algorithm, values of two parameters, the weighting factor and the temperature parameter, should be determined. The weighting factor α, in the equation (6) for similarity coefficient is set its value at a multiple of R which is $\sum_{i=1}^{M}\sum_{j=1}^{M} c_{ij} / \sum_{i=1}^{M}\sum_{j=1}^{M} d_{ij}$. To see the effect of α on grouping solutions, we tested α values such as $1R$, $2R$, $3R$ and $6R$. The temperature parameter τ, in equation (9) for updating input to the processing units, is set 0.02 based on pretest of several problems.

Srinivasan and Narendran[12] did a comparative study of the GRAFICS and ZODIAC[36] algorithms on a set of problems and reported that GRAFICS performs better based on grouping efficiency(CI) and grouping efficacy (CA). The grouping efficiency(CI) is the weighted average of the portion of '1's in diagonal blocks and the portion of balnks in off-diagonal blocks while the grouping efficacy (CA) is the portion of '1's in diagonal blocks with respect to the elements in the operational zone.

$$\mathrm{CI} = \pi \frac{e - EX}{e - EX + IB} + (1 - \pi)\frac{MN - (e - EX + IB) - EX}{MN - (e - EX + IB)}$$

$$(0 \le \pi \le 1) \qquad (11)$$

$$\mathrm{CA} = \frac{e - EX}{e + IB} \qquad (12)$$

Table 4. Comparison of the proposed algorithm with the GRAFICS algorithm

No. Source	size	e	GRAFICS		Proposed algorithm											
					$\alpha=R$			$\alpha=2R$			$\alpha=3R$			$\alpha=6R$		
			CI	CA	CI	CA	K	CI	CA	K	CI	CA	K	CI	CA	K
1. King and Nakornchai[35]	5×7	16	85.6	73.7	85.6	73.7	2	85.6	73.7	2	88.0	62.5	4	85.0	64.7	3
2. Waghodekar and Sahu[37]	5×7	20	74.5	60.9	77.1	68.0	2	74.5	60.9	3	80.0	50.0	4	80.0	50.0	4
3. Pannerselvam and Balasubramanian[38]	10×5	19	88.0	76.0	89.1	78.3	3	89.1	78.3	3	89.1	78.3	3	94.3	79.0	5
4. Seiffodini and Wolfe[7]	8×12	35	87.1	68.3	79.7	62.0	3	90.9	69.4	4	90.9	69.4	4	89.1	51.4	6
5. Chandrasekharan and Rajagopalan[29]	8×20	61	95.8	85.2	95.8	85.3	3	93.8	77.1	4	93.8	77.1	4	93.8	77.1	4
6. Chandrasedharan and Rajagopalan[39]	8×20	91	76.3	58.1	73.1	56.3	3	78.3	41.8	6	76.7	34.1	7	77.6	38.5	6
7. Srinivasan *et al.*[11]	10×20	49	100.0	100.0	100.	100.	4	100.	100.	4	100.	100.	4	100.	100.	4
8. Dewitte[40]	12×19	75	74.4	52.8	76.9	55.2	4	83.8	56.0	6	83.8	56.0	6	88.6	40.0	10
9. Seiffodini[8]	11×22	78	87.8	73.1	87.8	73.1	3	88.3	72.2	4	88.3	72.2	4	90.3	55.7	8
10. Askin and Subramanian[41]	14×23	58	82.5	64.4	83.7	66.7	4	83.7	66.7	4	83.7	66.7	4	89.1	72.9	6
11. Stanfel[42]	14×24	61	83.9	65.6	84.4	67.1	5	84.4	67.1	5	83.9	67.1	4	89.0	69.4	6
12. McCormick *et al.*[43]	24×16	85	73.4	45.5	74.5	46.9	6	83.9	50.0	10	89.7	49.4	12	91.0	46.0	15
13. Carrie[6]	24×18	88	75.6	48.9	72.7	44.1	5	76.1	46.9	7	79.8	50.4	9	88.9	50.0	14
14. Srinivasan *et al.*[11]	16×30	116	86.4	67.8	81.4	60.5	4	87.4	68.4	5	87.4	68.4	5	90.0	55.7	10
15. King[44]	16×43	126	79.4	54.4	79.9	54.5	6	79.9	54.5	6	83.0	55.4	8	90.6	51.1	12
16. Carrie[6]	20×35	136	87.8	75.1	88.1	75.7	4	88.1	75.7	4	88.1	75.7	4	88.8	76.0	6
17. McCormick *et al.*[43]	27×27	219	71.4	47.4	73.1	49.9	5	74.7	49.2	9	84.4	38.0	13	87.1	25.9	19
18. Chandrasekharan and Rajagopalan[45]	24×40	131	100.0	100.0	100.	100.	7	100.	100.	7	100.	100.	7	100.	100.	7
19. Chandrasekharan and Rajagopalan[45]	24×40	130	95.2	85.1	94.5	79.4	8	95.2	85.1	7	95.2	85.1	7	95.2	85.1	7
20. Chandrasekharan and Rajagopalan[45]	24×40	131	91.2	73.5	91.2	73.5	7	91.2	73.5	7	91.7	72.3	9	92.8	72.2	10
21. Chandrasekharan and Rajagopalan[45]	24×40	130	78.9	43.3	78.2	46.7	7	83.8	52.8	9	87.4	51.7	13	93.3	47.4	16
22. Chandrasekharan and Rajagopalan[45]	24×40	131	79.1	44.5	67.7	34.4	7	87.9	46.9	12	89.3	47.2	13	95.2	45.5	17
23. Chandrasekharan and Rajagopalan[45]	24×40	131	79.1	41.7	68.1	35.1	5	84.9	44.7	12	85.2	44.3	11	92.5	41.0	17
24. Kumar and Vanelli[46]	30×41	127	82.3	55.4	76.1	50.4	8	78.4	53.9	10	78.4	53.9	10	84.3	59.3	14
25. Carrie[6]	28×46	211	65.3	32.9	71.3	40.4	9	77.9	44.9	12	84.2	45.5	16	92.5	39.5	23
26. Stanfel[42]	30×50	154	85.2	56.3	72.0	43.5	5	73.6	45.9	6	77.3	50.0	9	85.4	57.5	12
27. Stanfel[42]	30×50	167	85.6	48.0	77.7	44.1	9	80.1	46.9	9	85.1	50.0	11	91.8	48.0	18
28. McCormick *et al.*[43]	37×53	977	76.1	52.2	74.1	59.9	8	76.6	53.6	11	77.5	46.3	15	78.6	40.1	22
29. King and Nakornchai[35]	36×90	303	72.9	37.0	65.4	30.8	14	68.9	35.6	16	76.2	42.6	19	86.4	46.0	27
30. Chandrasekharan and Rajagopalan[45]	40×100	420	71.9	35.6	90.3	76.2	9	95.1	84.0	10	95.1	84.0	10	95.1	84.0	10

where e = the number of '1's in the incidence matrix,

EX = the number of exceptional elements,

IB = the number of blanks in the diagonal blocks and

π = 0.5.

We compare the solutions by the proposed algorithm to those by GRAFICS and the results are in Table 4. Included in the table are the source from which it was found(source), the size of the incidence matrix(size), the number of '1's in the matrix (e) and the CI and CA values of solutions by the GRAFICS algorithm. Also, shown are CI and CA values of solutions by the proposed algorithm along with the number K of cells in the solutions.

In almost all the cases, the number of cells in the solution by the proposed algorithm increases as α increases. Problems with especially well-structured incidence matrix, such as problem 7 and 18, are not affected by α. In many problems, CI value seem to be better at higher α values. As the size of problems become bigger, there is a tendency that the highest scores in CI and CA are obtained at higher α values. With α fixed, CI and CA values of the proposed algorithm look competitive with those of GRAFICS. For all problems except problem 6, the proposed algorithm shows at least one solution with CI and CA values bigger than those of GRAFICS. It is possible to use the proposed algorithm to generate a set of different solution for a problem by varying the value of , then a solution is chosen that fits best in terms of the specific measures of goodness of grouping solution to be used or some managerial preferences.

6. Conclusions

This paper proposes a recurrent neural network based algorithm for the machine cells and part families formation problem. Newly designed similarity coefficients of machine pairs are used as connection weights between processing units in the neural network for forming machine cells.

The performance of the algorithm is compared on a set of problems with that of GRAFICS. The test results indicates that the proposed algorithm generates better solution in many cases. We may conclude that the algorithm could be regarded as a competitive one with the existing algorithms in generating effective solutions.

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