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Machine Cell Formation using A Classification Neural Network

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Abstract

The machine cell formation problem is the problem to group machines into machine families and parts into part families so as to minimize bottleneck machines, exceptional parts, and inter-cell part movements in cellular manufacturing systems and flexible manufacturing systems. This paper proposes a new machine cell formation method based on the adaptive Hamming net which is a kind of neural network model. To show the applicability of the proposed method, it presents some experiment results and compares the method with other cell formation methods. From the experiments, we observed that the proposed method could produce good cells for the machine cell formation problem.

Key words : *Group Technology, Cell Formation, Neural Networks, Classification, Adaptive Hamming Net*

1. Introduction

In batch-type production systems, a variety of items are produced in small quantities using various production processes. Conventional job-shop systems have been used for batch-type production where the same types of machines are grouped into machine centers and the items to be produced move around machine centers to complete the production processes. An alternative to the conventional job-shop systems is the cellular manufacturing system(CMS) based on the group technology(GT). GT is a philosophy or concept to increase production efficiency by identifying and exploiting the sameness or similarity among items of interest[3]. When GT is applied to the manufacturing field, it takes the form of CMS. Parts are grouped into part families based on the similarity in design and manufacturing and the machines which are needed to process the parts in a part family are put together to form a manufacturing cell. Unlike the job-shop system, machines in a manufacturing cell are dissimilar and cells are formed in a manner that all the parts in a family can be processed completely or nearly completely within a cell. CMS has the following benefits: reduction in working process inventory, setup time, throughput time and material handling cost, improvement in production quality.

In the design of CMS, two important issues should be addressed: the design of the system structure and the design of operation policies. For the design of the system structure, the first task is to identify parts to be processed in CMS, part processing operations with their sequences, and machines required to carry out all the operations. Then the cell formation follows which is to group the parts into part families and the machines into machine cells in which each cell is devoted to process parts in the corresponding part family. The selection of tools, fixtures and material handling equipments follows in the next step. Finally the layout of cells and the layout of machines in each cell are determined. Problems related to the design of operation policy are planning and scheduling, job design for operators, maintenance, interfacing the remaining manufacturing systems and so on.[4]

In this paper, we are interested in the cell formation stage in the design of system structure. For the cell formation, various methods have been developed[3-4][11-17]. We propose a neural network based cell formation method which uses the adaptive Hamming net.

This paper is organized as follows: Section 2 describes the cell formation problem, Section 3 presents the adaptive Hamming net. Section 4 introduces a cell formation method based on the adaptive Hamming net and Section 5 shows some experiment results. Finally, in Section 6, we draw the conclusions.

2. Cell Formation in CMS

Given the number of machines, the types and the capacities of each machine, the set of parts to be manufactured and the routing plans for each part, the aim of the machine-cell formation problem is to determine which machines should be grouped together to form cells[4].

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The problem is considered as one of block-diagonalizing the machine-part incidence matrix $X = [x_{ij}], i = 1, \ldots, \ldots, m; j = 1, \ldots, n$, so that each block identifies a machine cell and its corresponding part family, where

$$x_{ij} = 1 \quad \text{if part } j \text{ requires operation on machine } i$$
$$= 0 \quad \text{otherwise}$$

Elements comprising machine-part combinations that belong to more than one cluster are called bottleneck elements or exceptional elements. Parts corresponding to such elements require inter-cell movements.

For example, consider the machine-part incidence matrix X. It shows the initial incidence matrix for a problem having five parts and four machines.

$$X = \textit{Machine} \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \end{array} \begin{array}{c} \textit{Parts} \\ \begin{array}{ccccc} 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{bmatrix} 1 & 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 \end{bmatrix} \end{array}$$

Figure 1. Machine-part incidence matrix

Figure 2 shows the machine-part incidence matrix after it has been arranged so that the non-zero x_{ij}'s are clustered around the diagonal of the matrix.

$$X = \textit{Machine} \begin{array}{c} \\ 2 \\ 4 \\ 1 \\ 3 \end{array} \begin{array}{c} \textit{Parts} \\ \begin{array}{ccccc} 2 & 5 & 3 & 1 & 4 \end{array} \\ \begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 \end{bmatrix} \end{array}$$

Figure 2. Grouped incidence matrix

The matrix of Figure 2 can be partitioned into two diagonal submatrices. The upper submatrix defines a machine-part group consisting of machine 2, 4 and part 2, 5. The next diagonal submatrix consists of machines 1, 3 and parts 3, 1, 4. This is a two-cell solution. With an exception, all parts can be processed within their own cell. Part 3 which is assigned to the second cell requires some processing in the first cell(on machine 2). Machine 2 is the bottleneck machine and part 3 is the exceptional part. Part 3 leads to additional material handling cost. Taking such factors into consideration, the problem has been formulated by different researches in different ways, with performance measures that reflects inter-cell movement, material handling cost, machine loading or cell utilization. [9]

3. Adaptive Hamming Net

The adaptive Hamming net, which is proposed by Chen-An et al.[10], has a similar structure to the traditional Hamming net[1]. We can say that the adaptive Hamming net is an adaptive version of the Hamming net. Before describing the adaptive Hamming net, let's briefly review the Hamming net. The Hamming net for binary patterns computes the Hamming distance to each prototype and selects the prototype with the minimum Hamming distance. It consists of a feedforward excitatory network and a lateral inhibitory network. The main feature of the Hamming net is that it uses a MAXNET to pick the node with the maximum output value. This action is equivalent to MAXNET picking the prototype that has the least Hamming distance from the input pattern. Another feature of the Hamming net is that its synaptic weights are pre-stored and cannot be learned.

Unlike the fixed-weight Hamming net described above, the adaptive Hamming net can learn to adapt based on experience collected from previous training patterns. Furthermore, it is also able to learn new input patterns without forgetting old learned patterns. This property makes the neural model ideal for use as a pattern recognition machine in real-time environments. Another feature of the adaptive Hamming net is that it picks and chooses adequate prototypes through a similarity checking process.

An adaptive Hamming net is a two-layer neural network that consists of a matching score net with a threshold θ and a MAXNET. The matching score net is designed to map an input pattern into N matching scores, appearing respectively at the N output nodes of that net. For a binary-valued input, the matching scores are defined in terms of the inner product between the synaptic weight matrix and the input pattern. After multiplying the N matching scores by a set of weights, one can use a MAXNET to select an adequate category for which the weighted matching score is the highest. If an adequate match is found, the weights connected to that net are updated. Learning within an adaptive Hamming net either refines the prototype of a previously established category or assigns the input pattern to a new category. When the input pattern is familiar, the system will access a previously learned category. When the input pattern is novel, the system will memorize it.

The architecture of an adaptive Hamming net is shown schematically in Figure 3. The net contains n input layer neurons, N hidden layer neurons, and N output layer neurons. To carry out fast learning of stable recognition categories in response to arbitrary sequences of binary input patterns, the matching score between an input pattern and an existing prototype must be larger than a certain threshold. This means that learning occurs only when the input pattern and the stored prototype are sufficiently similar. The threshold level of the matching score net is autotuned by a linear.combiner, as shown in Figure 3. This is different from Hamming net, which has a predefined threshold level. The threshold level of the adaptive Hamming net is dependent upon the input pattern. This enables the adaptive Hamming net to add new prototypes to an existing set of memorized prototypes without retraining the entire network.

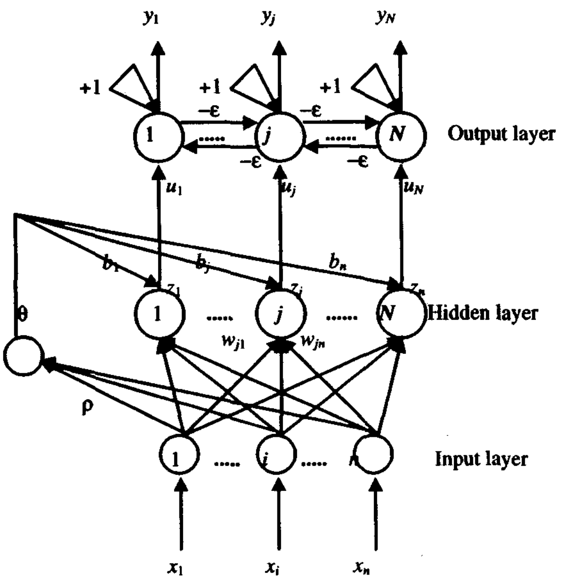

Figure 3. Adaptive Hamming Net

The adaptive Hamming net and the fixed-weight Hamming net have a similar architecture, but use different weight learning and thresholding techniques. In a traditional Hamming net, the prototype patterns are directly assigned to the weights and the threshold value is fixed. In contrast, in an adaptive Hamming net, the weights can be refined by a similar input pattern or directly assigned by a novel pattern and the threshold value is controlled by the input pattern and vigilance parameter σ. Unlike the fixed-weight Hamming net, the matching scores in the adaptive Hamming net are also weighted by a set of parameters.

4. Cell Formation based on the Adaptive Hamming Net

The adaptive Hamming net has the capability of classifying given patterns into several categories based on the similarity among the patterns. The machine cell formation problem can be considered as a classification problem in which machines to process a similar group of parts are classified into the same category. In this perspective, we can apply the adaptive Hamming to the machine cell formation problem.

Suppose that there is a cell formation problem with n parts and m machines of which processing information is given by mxn incidence matrix. When we regard the cell formation problem as a machine classification problem, the part information for each machine becomes a pattern. That is, each row vector in the incidence matrix becomes a pattern. Thus, from an mxn incidence matrix, we have m patterns to be classified.

As mentioned in Section 3, the adaptive Hamming net consists of 3 layers. For a cell formation problem given with an mxn machine-part incidence matrix, we can solve the problem with the following adaptive Hamming net: Since each pattern contains n elements, the input layer is made of n neurons. Both the hidden layer and the output layer have the same number of neurons and each neuron corresponds to a prototype to be stored in the net. Thus both layers have the number of neurons larger than or equal to the desired number of cells.

To adjust the weights for classification, the built net performs the following operations:

Step 1. Initialize the weights on the net.

$$W_{ij}=1, \quad i=1,\cdots,N, j=1,\cdots,n$$
$$b_j=\lambda_j, \quad j=1,\cdots,N$$
$$\lambda_N < \cdots < \lambda_j < \cdots < \lambda_1 < \frac{1}{\alpha+n}$$

Step 2. Present an input pattern(a row vector in the given incidence matrix) on the input layer.

$$X=[x_1,\cdots,x_n], \quad x_i \in \{0,1\}$$

Step 3. Evaluate the similarity of the input pattern with existing prototypes.

$$z_j = f_\theta(\sum_{i=1}^{n} W_{ji}x_i)$$
$$f_\theta = \begin{cases} 1 & if\ x>\theta \\ 0 & otherwise \end{cases}$$
$$\theta=\sum_{i=1}^{n}\rho x_i, \quad 0\le\rho\le1$$

Step 4. Apply weighting operation to the evaluated similarity values.

$$u_j=b_jz_j$$

Step 5. Select the prototype for the input pattern.

$$j^*=\max_{j=1,\cdots,N} \arg\ u_j$$

Step 6. Update the weights related to the selected prototype.

$$W_{j^*i}(t+1)=W_{j^*i}(t)x_i$$
$$b_{j^*}(t+1)=\frac{1}{\alpha+z_{j^*}}, \qquad 0<\alpha\le1$$

Step 7. If it satisfies the given termination condition, stop the learning process.

Otherwise, go to Step 2.

With the above algorithm, we train the built adaptive Hamming net for the given incidence matrix data. To solve the machine-cell formation problem, we use the learned net in the following ways: We present each row vector of the incidence matrix to the net and get the identifier of the prototype which produces the maximum value. The machines with the same prototype identifier consist of a machine cell. The parts belonging to a machine cell come to the corresponding part family. When there are some exceptional parts, we assign the parts to the part family that causes to produce fewer exceptional parts by the assignment.

5. Experiment Results

To show the applicability of the proposed adaptive Hamming net-based method, we have carried out several experiments for the problems found in the literature. Table 1 shows the test problems used in the experiments.

Table 1. Test Problems

No	Source	Size
1	Srinvasan [11]	10x20
2	Chan and Milner[16]	15x10
3	Grefenstette [17]	15x30
4	Carrie [14]	20x35
5	Kumar [15]	15x30
6	Chandrasekharan [7]	8x20
7	Seifoddini [13]	11x22
8	Stanfel [12]	14x24
9	Chandrasekharan [7]	24x40

Table 2 exemplies the machine-part incidence matrix of a 10(machines)x20(parts) test problem used in the Srinvasan's works[11]. In the matrix, the rows indicate the machines and the columns indicate the parts to be processed.

Table 2. Machine-Part incidence matrix of Srinvasan data[11]

	00000000011111111112 12345678901234567890
1	10010010000000000000
2	01101001010000000000
3	01101001010000000000
4	10010010000000000000
5	00000000000011101101
6	10010010000000000000
7	00000100101100010010
8	00000100101100010010
9	00000000000011101101
10	00000100101100010010

Table 3 shows the cell-formation result obtained by the proposed adaptive Hamming net-based cell-formation method. From Table 3, we can see that the following four groups are formed:

Group 1 : machines {5, 9} parts {13, 14, 15, 17, 18, 20}
Group 2 : machines {1, 4, 6} parts {1, 4, 7}
Group 3 : machines {7, 8, 10} parts {6, 9, 11, 12, 16, 19, }
Group 4 : machines {2, 3} parts {2, 3, 5, 8, 10}

Table 3. Cell formation Result

	11111200000111100001 34578014769126923580
5	11111100000000000000
9	11111100000000000000
1	00000011100000000000
4	00000011100000000000
6	00000011100000000000
7	00000000011111100000
8	00000000011111100000
10	00000000011111100000
2	00000000000000011111
3	00000000000000011111

Table 4 shows a 20(machines)x35(parts) test problem of Carrie's work[14]. Table 5 shows the cell formation results by the proposed method., where there are some exception parts which can not belong to a specific group.

Table 4. Machine-Part incidence matrix of the Carrie data[14]

Table 5. Cell formation result

	00000000011111111112222222222333333 12345678901234567890123456789012345
1	10100000000000000001001010000000000
2	01000010010110000100000100100010000
3	10101000000000101000000000001010000
4	01000010000110000000000100100000000
5	00000001000001010000000000000000010
6	00000001000001010010010001000000010
7	10101000000000101001001000000000000
8	10101000000000101001001010001000000
9	00000001000001000010010001000000000
10	00000001000001010010010001000000000
11	0001010010100000000010000001010101001
12	00010100101000000000100000000000100
13	01000000000110000000001000000000000
14	01000010010110000100000100100010000
15	00010100101000000000100000010100000
16	00010100101000000000100000010101000
17	10101000000000101000001010001000000
18	01000000010110000100000100000010000
19	00010100101000000000100000010101000
20	00000001000001000010001001000000000

	00111122301131220001223333002201122 27023847184649264691180253130555793
2	11111111100000000000000000000000000
4	11011011000000000000000000000000000
13	10011000000000000000000000000000001
14	11111111100000000000000000000000000
18	10111110100000000000000000000000000
5	00000000011110000000000000000000000
6	00000000011111110000000000000000000
9	00000000011001110000000000000000000
10	00000000011101110000000000000000000
20	00000000011001010000000000000000001
11	00000000000000001111111110000000000
12	00000000000000001111100001000000000
15	00000000000000001111111000000000000
16	00000000000000001111111100000000000
19	00000000000000001111111100000000000
1	00000000000000000000000000111100001
3	00000000100000000000000000110011110
7	00000000000000000000000000111011101
8	00000000000000000000000000111111111
17	00000000000000000000000000110111111

To show the effectiveness of the proposed method, we chose the following three methods:

- Rank Order Clustering(ROC)
- Bond-Energy Algorithm(BEA)
- Similarity Coefficient Method(SCM)

These methods are famous methods in the group technology and their good reference is cited in [4].

To compare the grouping efficiency for the proposed adaptive Hamming net-based method (AHN) with that of the above-mentioned three methods, we use the following three grouping effectiveness measures:

$$\eta_1 = \frac{e_d}{\sum_{l=1}^{C} M_l N_l}$$

$$\eta_2 = 1 - \frac{e_0}{nm - \sum_{l=1}^{C} M_l N_l}$$

$$\eta = q\eta_1 + (1-q)\eta_2$$

n	the total number of parts
m	the total number of machines
M_l	the number of machines in the l-th cell
N_l	the number of parts in the l-th cell
e_d	the number of '1' in the diagonal blocks
e_0	the number of '1' in the off-diagonal blocks
q	the weighting factor ($0 \le q \le 1$)
C	the number of cells

η_1 is the measure for the within-group utilization that measures how much the machines of each cell handle the parts of the corresponding part family. η_2 is the measure for the least inter-cell movement which measures how few exceptional parts exist. The measures η_1 and η_2 reflect different aspects of the grouping effectiveness. η is the measure for the grouping efficiency which reflects two aspects of η_1 and η_2. The larger values the measures have, the better the grouping effectiveness becomes.

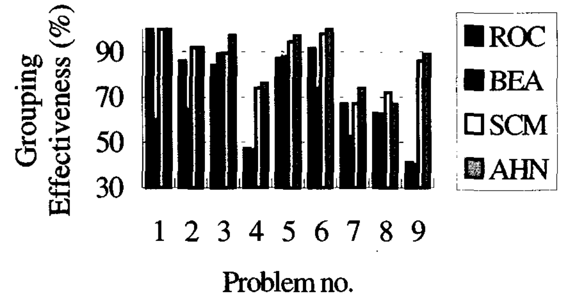

Figure 4. Grouping Effectiveness Measure η_1

Figures 4, 5, and 6 show the experiment results with respect to the three grouping effectiveness measures η (at q = 0.5), η_1, and η_2, respectively. From these experiment results, we can see that the proposed method(AHN) is better than ROC and BEA methods for all test problems. Except the problem 8, the proposed method gives better grouping than SCM does. The difference of effectiveness between SCM and AHN is so small even for the test problem 8. We can say that the proposed method is a good cell-formation method.

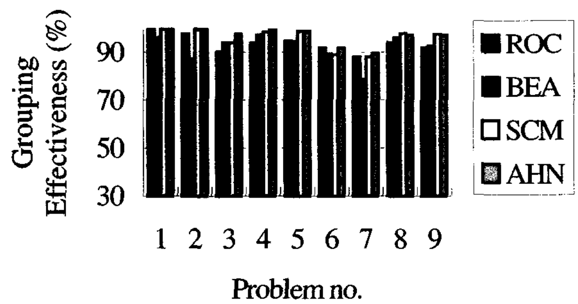

Figure 5. Grouping Effectiveness Measure η_2

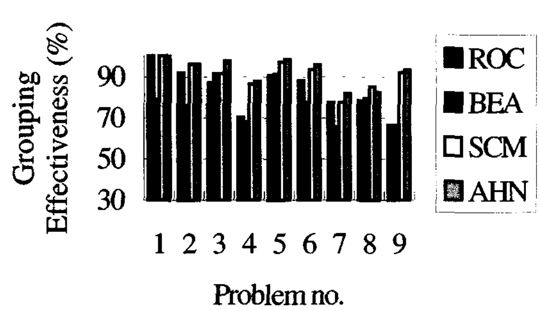

Figure 6. Grouping Effectiveness Measure η

6. Conclusions

The cell formation problem is an important issue in the cellular manufacturing systems. This paper proposed an adaptive Hamming net-based method to solve the cell formation problem. To show the applicability of the proposed method, we compared the method with other existing methods for several test problems. From the experiments, we can see that proposed method is effective better than or equal to the compared cell formation methods. Thus we can say that the proposed method is a good alternative to the existing methods for cell formation. In this paper, we have considered only the cell formation problem without the routing plan information. Thus we need further study on the cell formation problem with the routing plan information.

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