Manufacturing cell formation using the Bees Algorithm

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Abstract

Cellular manufacturing has received increasing attention in recent years. The key problem in designing cellular manufacturing systems is cell formation, which is concerned with grouping parts with similar processing requirements into part families and associated machines into machine cells. This paper presents a novel approach for solving the cell formation problem. The proposed approach is based on a new optimisation technique called the Bees Algorithm that mimics the food foraging behaviour of honey bees. Experimental results indicate that the proposed approach is very effective for large-scale problems.

Keywords: Group Technology, Cell Formation, Bees Algorithm, Combinatorial Optimisation

1. Introduction

Manufacturing industry is under intense pressure from the increasingly competitive global marketplace. Shorter product life-cycles, unpredictable demands, and diverse customer needs have forced manufacturing firms to operate more efficiently and effectively in order to adapt to changing requirements. Traditional manufacturing systems, such as job shops and flow lines, cannot handle such environments. Cellular manufacturing (CM), which incorporates the flexibility of job shops and the high production rate of flow lines, has emerged as a promising alternative for such cases [1].

CM is the application of the concept of group technology (GT) in manufacturing systems. GT is a manufacturing philosophy that exploits similarities in product design and production processes. A fundamental issue in CM is the determination of part families and machine cells. This issue is known as the cell formation (CF) problem. The CF problem involves the decomposition of a manufacturing system into cells. Part families are identified such that they are fully processed within a cell. The cells are formed to capture the advantages of GT such as reduced setup times, reduced in-process inventories, improved product quality, shorter lead times, reduced tool requirements, improved productivity, and better overall control of operations [2].

The CF problem has long been recognised as the most challenging problem in realising the concept of cellular manufacturing. It belongs to the class of NP-hard problems, which means that an increase in the problem size will cause an exponential increase in the computational time for all prevalent optimisation techniques. Many methods to solve this problem have been developed [3, 4], including array-based methods, clustering methods, mathematical programming-based methods, graph theoretic methods, and artificial intelligence-based methods.

This paper presents an application of a new population-based optimisation algorithm called the Bees Algorithm to form machine-part cells. The Bees Algorithm is inspired by the food foraging behaviour of honey bees and performs a kind of neighbourhood search combined with random search to enable it to locate the global optimum. The algorithm has been successfully applied to different optimisation problems including the training of neural networks for control chart pattern recognition [5], identification of wood defects [6], overcoming the local optimum problem of the *k*-means clustering algorithm [7] and job scheduling [8].

The paper is organised as follows. Section 2 presents the cell formation problem. Section 3 describes the core ideas of the proposed CF approach. Computational results are reported in section 4. Section 5 concludes the paper and gives suggestions for future work.

2. The Cell Formation problem

The CF problem solved here is to simultaneously group machines and their corresponding part families into cells so that intercellular movements are minimised. It can be formulated by using an M x N machine-part incidence matrix, $A = [a_{ij}]$, where a_{ij} is a binary variable that takes the value of 1 if part j requires processing on machine i, and 0 otherwise. The problem is equivalent to decomposing A into a number of diagonal blocks of submatrices, where each diagonal block represents a manufacturing cell. The effectiveness of the decomposition can be determined by a normalised bond energy measure denoted as α in Eq. 1 [9].

$$\alpha = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N-1} a_{ij}a_{i,j+1} + \sum_{i=1}^{M-1}\sum_{j=1}^{N} a_{ij}a_{i+1,j}}{\sum_{i}^{M}\sum_{j}^{N} a_{ij}} \tag{1}$$

The objective is to group parts and machines into clusters by sequencing the rows and columns of a machine-part incidence matrix, so as to maximise the bond energy measure of the incidence matrix. In the next section, a new method to solve the CF optimisation problem is described. The new method adopts the Bees Algorithm as it has proved to have a more robust performance than other intelligent optimisation methods for a range of complex problems [10, 11].

3. Cell Formation using the Bees Algorithm

The proposed CF algorithm utilises the ability of the Bees Algorithm to search for the appropriate groups of part families and machine cells such that the bond energy metric α (Equation 1) is maximised. Figure 1 shows the basic steps of the CF algorithm, which are also followed in the Bees Algorithm. These steps are described in detail below.

1. Initialise population with random solutions.
2. Evaluate fitness of the population.
3. While (stopping criterion not met) //Forming new population.
4. Select sites for neighbourhood search.
5. Recruit bees for selected sites (more bees for the best *e* sites) and evaluate fitnesses.
6. Select the fittest bee from each site.
7. Assign remaining bees to search randomly and evaluate their fitnesses.
8. End While.

Fig. 1. Basic steps of the Bees-Algorithm

The proposed algorithm requires a number of parameters to be set, namely, number of scout bees (*n*), number of sites selected for neighbourhood search (out of *n* visited sites) (*m*), number of top-rated (elite) sites among *m* selected sites (*e*), number of bees recruited for the best *e* sites (*nep*), number of bees recruited for the other (*m-e*) selected sites (*nsp*), and the stopping criterion.

The algorithm starts with an initial population of *n* scout bees. Each bee is a symbolic string representing the sequence of machines and parts that appear in a machine-part incidence matrix (see Fig. 2). For an M x N machine-part incidence matrix, a string with a length of $M + N$ is needed to encode each candidate solution. The first M bits of the string represent the sequence of machines that appear in the rows of the incidence matrix, while the last N bits of the string represent the

m/n	1	2	3	4	5	6
1	0	1	1	0	0	1
2	0	1	0	1	1	0
3	1	0	0	1	1	1
4	1	1	1	0	0	0
5	0	0	1	0	1	1
6	1	0	0	1	1	0

Fig. 2. Representation of a machine-part incidence matrix.

sequence of parts appearing in the columns of the matrix.

In step 2, the fitness computation process is carried out for each site visited by a bee by calculating the bond energy measure α (see Eq. 1).

In step 4, the *m* sites with the highest fitnesses are designated as “selected sites” and chosen for neighbourhood search.

In steps 5 and 6, the algorithm conducts searches around the selected sites, assigning more bees to search in the vicinity of the best *e* sites. Selection of the best sites can be made directly according to the fitnesses associated with them. Alternatively, the fitness values are used to determine the probability of the sites being selected. Searches in the neighbourhood of the best *e* sites which represent the most promising solutions are made more detailed by recruiting more bees for the best *e* sites than for the other selected sites. Together with scouting, this differential recruitment is a key operation of the Bees Algorithm.

In step 6, for each patch only the bee with the highest fitness will be selected to form the next bee population. In nature, there is no such a restriction. This restriction is introduced here to reduce the number of points to be explored.

In step 7, the remaining bees in the population are assigned randomly around the search space to scout for new potential solutions.

At the end of each iteration, the colony will have two parts to its new population: representatives from the selected patches, and scout bees assigned to conduct random searches. Steps 4-7 are repeated until either the best fitness value has stabilised or the specified maximum number of iterations has been reached.

4. Experimental Results

In this section, two examples are first used to illustrate the operation of the proposed CF algorithm. Then, eight benchmark CF problems with different sizes are used to test the effectiveness of the algorithm. The results obtained are compared to the best-known solutions reported in the literature. The grouping efficiency measure [3], ε, is adopted to assess the quality of the solutions. The ε measure is defined as follows:

$$\varepsilon = \frac{n_1}{\sum_{k=1}^{K} M_k N_k} - \left(1 - \frac{n_1}{n_1 + n_2}\right) \qquad (2)$$

where n_1 is the number of non-zero entries within the manufacturing cells in the machine-part incidence matrix; K is the number of manufacturing cells formed; M_k and N_k (k = 1, 2,…, K) are the number of the machines and parts allocated to the manufacturing cell k; n_2 is the number of exceptional elements in the machine-part incidence matrix.

In Equation 2, the first term represents the cell density and can be written as:

$$\varepsilon_1 = \frac{n_1}{\sum_{k=1}^{K} M_k N_k} \qquad (3)$$

A high value of ε_1 indicates that the machines and parts in each manufacturing cell are very similar to one another.

The second term represents the intercellular material flows and can be given as:

$$\varepsilon_2 = 1 - \frac{n_1}{n_1 + n_2} \qquad (4)$$

A low value of ε_2 will result if less exceptional elements exist in the incidence matrix.

According to Equation 2, the value of the grouping efficiency measure, ε, ranges from -1 to 1. The higher this value, the better the formed machines and parts groups.

In the first illustrative example [9, 12], a 16 x 30 machines-parts incidence matrix is utilised. The initial configuration of the matrix is shown in Figure 3. The parameters of the proposed CF algorithm are set as follows: n = 100, m = 40, e = 20, nep = 200, nsp = 100 and maximum number of iterations = 1000. By sequencing the order of rows (machines) and columns (parts) of the incidence matrix, the resulting configuration of the matrix is shown in Figure 4. In order to maximise the bond energy of the matrix, the

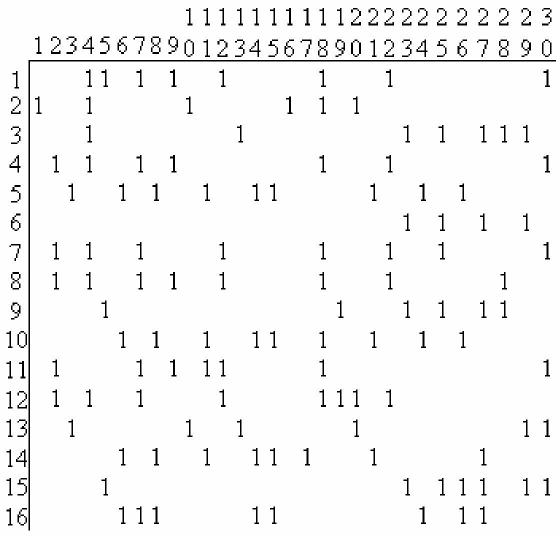

Fig. 3. The initial configuration of the machine-part incidence matrix of the first illustrative example.

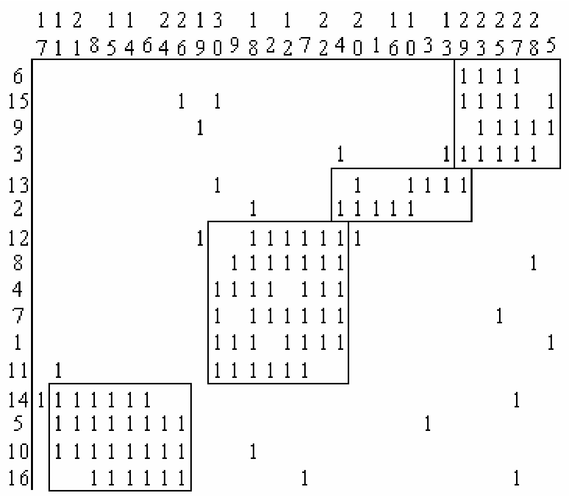

Fig. 4. The composition of the manufacturing cells for the first illustrative example.

machines and parts are grouped into 4 manufacturing cells. The bond energy measure, α, of the final solution is 1.301. The cell density measure, ε_1, is 0.816 which indicates that the machines and parts in the manufacturing cells are very similar. The measure of intercellular material flows, ε_2, is 0.155. The corresponding grouping efficiency of the final solution, ε, is 0.661, which is better than the best solution given in [9, 12].

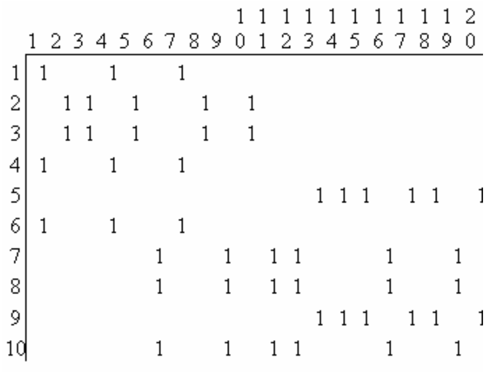

Fig. 5. The initial configuration of the machine-part incidence matrix of the second illustrative example.

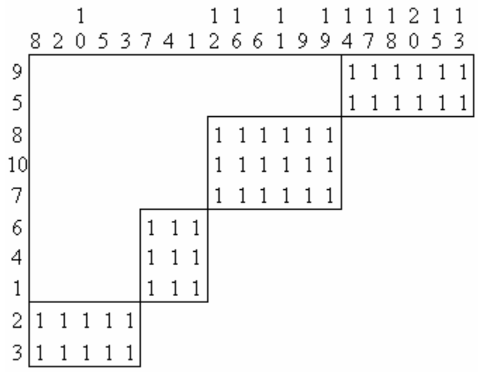

Fig. 6. The composition of the manufacturing cells for the second illustrative example.

In the second illustrative example [9, 12], a 10 x 20 machines-parts incidence matrix (shown in Figure 5) is employed. The parameters of the proposed CF algorithm are set as follows: n = 100, m = 40, e = 20, nep = 200, nsp = 100 and maximum number of iterations = 100. The final configuration of the incidence matrix is shown in Figure 6. The machines and parts are grouped into 4 manufacturing cells. The bond energy of the final solution is 1.388. The cell values of ε_1, ε_2, and ε of this solution are 1.000, 0.000, and 1.000 respectively. This solution is exactly the same as that suggested in [9, 12].

In order to further test its effectiveness, the proposed CF algorithm is applied to 8 test problems. The results of the CF algorithm are compared against those of the best-known solutions. All the problems are formulated by 0-1 machine-part incidence matrices. The parameters of the CF algorithm are set to n = 100,

Table 1
Results of solving 8 well-known benchmark CF problems from the literature.

No	Literature references	Size	*K*	Best-known solutions			Results from the CF algorithm			
				ε_1	ε_2	ε	α	ε_1	ε_2	ε
1	[13]	7x11	3	0.760	0.095	0.665	1.095	0.760	0.095	0.665
2	[13]	7x11	3	0.760	0.000	0.760	1.053	0.760	0.000	0.760
3	[12]	10x20	4	1.000	0.000	1.000	1.388	1.000	0.000	1.000
4	[14]	20x35	4	0.760	0.015	0.745	1.555	0.794	0.029	0.760
5	[15]	24x40	7	1.000	0.000	1.000	1.515	1.000	0.000	1.000
6	[15]	24x40	7	0.939	0.075	0.864	1.423	0.925	0.061	0.864
7	[15]	24x40	7	0.855	0.138	0.717	1.192	0.860	0.153	0.707
8	[9]	40x100	10	0.910	0.086	0.824	1.471	0.910	0.077	0.833

m = 40, e = 20, *nep* = 200, *nsp* = 100 and maximum number of iterations = 100.

Table 1 summarises the results obtained. As can be seen from the table, the proposed CF algorithm has produced similar results to those of the best-known solutions for problems 1, 2, 3, 5 and 6. In problem 7, the grouping efficiency measure, ε, is slightly reduced from 0.717 to 0.707. However, the CF algorithm achieved better results for problems 4 and 8. In problem 4, the cell density measure, ε_1, has been increased from 0.760 to 0.794, while the measure of intercellular flows, ε_2, has been increased from 0.015 to 0.029. This has led to an increase of the grouping efficiency, ε, from 0.745 to 0.760. In problem 8, which involves a 40 x 100 machine-part incidence matrix, the value of ε_2 has been reduced from 0.086 to 0.077. The value of ε_1 has also been increased from 0.903 to 0.910. Therefore, the grouping efficiency has been improved (increased) from 0.815 to 0.833.

5. Conclusions and Future Work

This paper has presented a new approach for simultaneous formation of part families and machine cells for cellular manufacturing systems. The approach is based on the Bees Algorithm, which is capable of performing local and global search simultaneously. Experimental results on a set of benchmark manufacturing cell formation problems obtained from the literature have indicated that the proposed approach is very effective in generating optimal solutions to the manufacturing cell formation problem, and is therefore a useful tool for the design of cellular manufacturing systems.

Several opportunities exist for further research. First, in this study the cell formation model only considers machining operations of parts presented by a binary machine-part incidence matrix. There is a need to take into account other manufacturing factors such as production volume, alternate routings and process sequences. Second, the Bees Algorithm employs a large number of tunable parameters which may be difficult for the user to select. An important line of research, therefore, is to find ways to help the user choose appropriate parameters.

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