A Migrating Birds Optimization algorithm for Machine-Part Cell Formation Problems

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Abstract. Machine-Part Cell Formation Problems consists in organizing a plant as a set of cells, each one of them processing machines containing the same type of parts. In recent years, different meta-heuristic have been used to solve this problem. This paper addresses the problem of Machine-Part Cell Formation by using the Migrating Birds Optimization algorithm. The computational experiments show that in most of the benchmark problems the results obtained from the proposed approach are better than those obtained by other methods which are reported in the literature.

Keywords: Cell formation problem, Nature-inspired algorithms, Migrating birds optimization, Meta-heuristics

1 Introduction

Cellular Manufacturing is an organizational approach based on Group Technology [17]. The purpose of the manufacturing cell is to divide the plant in a set of cells. This identification process requires an effective approach to form part families so that similarity within a part family can be optimized. According to Selim et al. [23], clustering analysis is one of the most used methods for manufacturing cell design methods. The formation of cells is known to be NP-complete and there is still the challenge of creating an efficient grouping method.

This paper focuses on solving machine-part cell formation problems. We use a new nature-inspired meta-heuristic for combinatorial optimisation problems called Migrating Birds Optimization (MBO) [7], that has successfully been used to solve complex optimization problems such as: A hybrid flowshop scheduling with total flowtime minimisation [19], Closed loop layout with exact distances in flexible manufacturing systems [18], Obstacle neutralization problem [1].

We perform tests to resolve machine-part cell formation problem using MBO and compared with Simulated Annealing (SA) [4,29] and Particle Swarm Optimization (PSO) [9,8], obtaining encouraging results. This paper is organized as follows: Section 2 presents the related work. Section 3 describes and models the machine-part cell formation problems; Section 4 gives an overview of MBO; Section 5 presents and discuss the experimental results. Finally, we conclude and give some directions for future work.

2 Related Work

The machine-part cell formation has emerged in the last two decades as innovation for manufacturing strategy, which includes the advantages of serial production. However, the independence between cells is difficult to produce in practice, because some parts need to be processed in more than one machine. Therefore, the objective of the machine-part cell formation problems, consists on grouping machines and parts so as to minimize the flow between them.

Several investigations have been carried out for the problem. Burbidge [5] has been one of the early researchers focused on the problem of machine-part cell formation, in which he focused on the implementation of a new production strategy focused on a reduction of flows and costs. Some methods are just trying to find a family of parts, resulting in a partial solution; because the identification of part families require machines to process all parts within the same cell. This is modeled as a p-median problem or one can take advantage of the special structure of clustering matrices and solve it by the rank energy algorithm [13]. In addition, there have been other relevant research to solve the machine-part cell formation problem as a linear formulation of the problem [4], simultaneous grouping of parts and machines in cellular manufacturing systems in an integer programming approach [10] and a comparative study of similarity coefficients and clustering algorithms in cellular manufacturing [22].

The problem of machine-part cell formation has had two complementary lines of research. These are organized into two groups: Global optimization and Approximate methods. The global optimization is to analyze the entire search space, in order to guarantee a global optimum, as a result, the computational cost in terms of memory and time consumed is much higher. In this group we find research based on Linear programming [20], Goal programming [24], Constraint programming [26,6] and Boolean satisfiability [25]. By contrast, the approximate methods as meta-heuristic focus on finding an approximate solution to a given amount of time; therefore, they can not guarantee a global optimum. Duran et al. proposed to Particle Swarm Optimization algorithm enhanced with a data mining technique for manufacturing cell design [9]. Simulated Annealing Approaches for machine-part cell formation problems can be found in [4] and [29], respectively. Other research using meta-heuristics are: Tabu seach [16,28], Ant colony optimization [14], Genetic algorithms [27,12].

In this paper, we focus on solving the problem machine-part cell formation using a metaheuristic called Migrating Birds Optimization, which to our knowledge has not yet been reported.

3 Problem description

In this work, we model the machine-part cell formation problem by using an array-based clustering approach. The main idea is to represent the processing requirements of parts on machines through an incidence matrix named machine-part (MxP). This matrix holds binary domains and is denoted as $A = a_{ij}$, where:

$$a_{ij} = \begin{cases} 1 \text{ if part } j \text{ visits machine } i \text{ for the processing;} \\ 0 \text{ otherwise.} \end{cases}$$

Let us note that when a machine-part incidence matrix is contructed, cells or part of families are easily visible. The main objective for machine-part cell formation problems is the organization of set of machines and parts in groups so that the number of intercell transportation is minimized. Fig. 1 presents an example of diagonal block formation. This example corresponds to a machine-part cell formation problem with the following parameters: 5 machines, 7 parts, an incidence matrix a_{ij} (left matrix in Fig. 1), $M_{max} = 3$ for 2 cells. Finally, assignment matrices y_{ik} and z_{jk} can be observed in Fig. 2, the optimum value obtained is 0 and the new incidence matrix a_{ij} constructed from the results of y_{ik} and z_{jk}, has to be transformed into a solution matrix that has a block diagonal structure (right matrix in Fig. 1).

	P1	P2	P3	P4	P5	P6	P7
M1	0	1	0	1	1	1	0
M2	1	0	1	0	0	0	0
M3	1	0	1	0	0	0	1
M4	0	1	0	1	0	1	0
M5	1	0	0	0	0	0	1

		P1	P3	P7	P2	P4	P5	P6
Cell 1	M2	1	1	0	0	0	0	0
	M3	1	1	1	0	0	0	0
	M5	1	0	1	0	0	0	0
Cell 2	M1	0	0	0	1	1	1	1
	M4	0	0	0	1	1	0	1

Fig. 1. An example of cell formation.

A mathematical formulation of machine-part cell formation problem is given by Boctor [4]. The optimization model is stated as follows, Let:

- M: the number of machines.
- P: the number of parts.

	Cell 1	Cell 2
M1	0	1
M2	1	0
M3	1	0
M4	0	1
M5	1	0

	Cell 1	Cell 2
P1	1	0
P2	0	1
P3	1	0
P4	0	1
P5	0	1
P6	0	1
P7	1	0

Fig. 2. Machine-Cell matrix y_{ik} and Part-Cell matrix z_{jk}.

- C: the number of cells.
- i: the index of machines ($i = 1, \ldots, M$).
- j: the index of parts ($j = 1, \ldots, P$).
- k: the index of cells ($k = 1, \ldots, C$).
- M_{max}: the maximum number of machines per cell.
- $A = a_{ij}$: the $M \times P$ machine-part incidence matrix.
- y_{ik}: the $M \times C$ machine-cell matrix, where:

$$y_{ik} = \begin{cases} 1 \text{ if machine } i \in \text{cell } k; \\ 0 \text{ otherwise;} \end{cases}$$

- z_{jk}: the $P \times C$ part-cell matrix, where:

$$z_{jk} = \begin{cases} 1 \text{ if part } j \in \text{cell } k; \\ 0 \text{ otherwise;} \end{cases}$$

The problem is represented by the following mathematical model:

$$\texttt{minimize} \quad \sum_{k=1}^{C} \sum_{i=1}^{M} \sum_{j=1}^{P} a_{ij} z_{jk} (1 - y_{ik}) \tag{1}$$

Subject to:

$$\sum_{k=1}^{C} y_{ik} = 1 \quad \forall_i \tag{2}$$

$$\sum_{k=1}^{C} z_{jk} = 1 \quad \forall_j \tag{3}$$

$$\sum_{i=1}^{M} y_{ik} \leq M_{max} \quad \forall_k, \tag{4}$$

4 Migrating birds optimization

4.1 Natural migration of birds

The migrating birds optimization imitates the behaviour of bird migration in V-shaped flight formation when season changes. There is a bird that is the leader of the flock, which is followed by other birds, that are going after him on his right and left hand, so that in the sky you can see the classic V-formation [3]. In this formation of migrating birds, some parameters like Wing-Tip Spacing (WTS), angle of the V-formation (α), maximum width of the wing (w), depth and wing span (b) are important to form an effective V-formation (show in Fig 4). To determine the WTS some experiments [15,2] have been done, but finally the best optimal value of WTS was obtained by Hummel and Beukenberg [11], which it is formulated as $\mathrm{WTS}_{opt} = -0.05b$. In addition to the WTS, energy saving flight can also be affected by the depth (the distance of a bird flying bird behind leader position). The vortex sheet behind a fixed wing in constant flight, level winds to form two vortices (show in Fig 3) concentrated in two lengths of rope of the wing [21]. Therefore, the optimum depth can be formulated as $D_{opt} = -2w$.

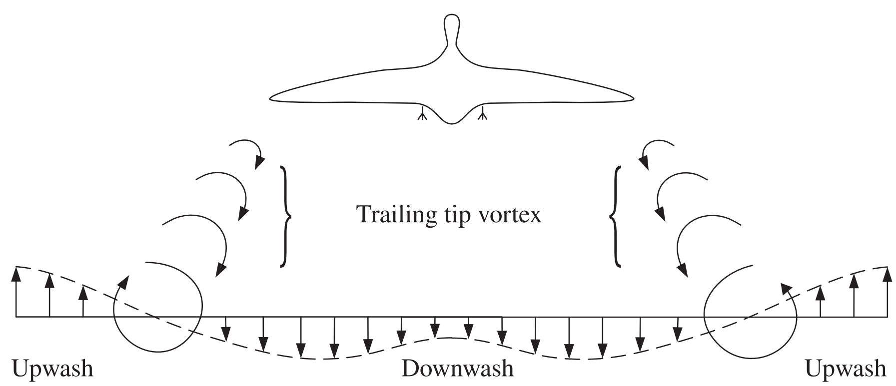

Fig. 3. Regions of upwash and downwash created by trailing vortices.

4.2 Migrating birds optimization method

The migrating birds optimization (MBO) starts with a number of initial solutions corresponding to birds in a V-formation. The initial population is composed of n solutions that are randomly generated in the feasible solution space. Starting with the first solution (corresponding to the leader bird) and progressing on the lines towards the tails. Each solution try to be improved by its neighbor solutions. If the best neighbor solution brings an improvement, the current solution is replaced, otherwise, the leader stays unchanged. Also there is a benefit, which

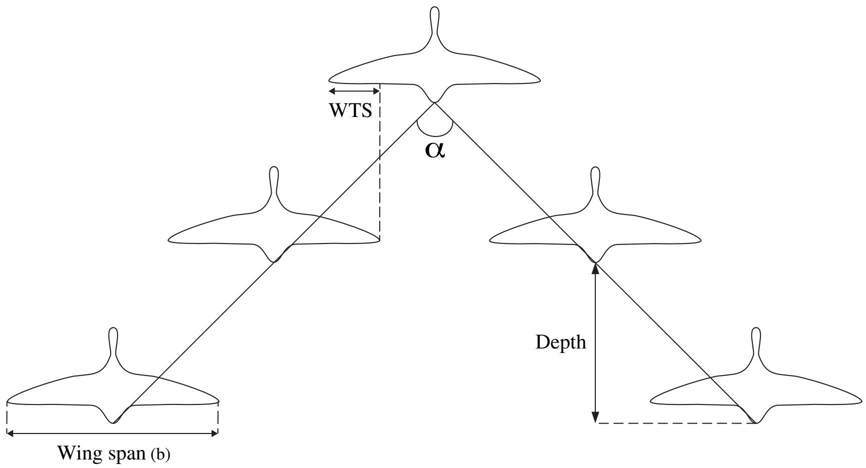

Fig. 4. The V-formation.

is a mechanism for the solutions (birds) to share unused solutions. This mechanism consist in sharing with the unused neighbors the solutions that follow in the flock. In other words, a solution evaluates a number of its own neighbors and a number of neighbors of the previous solution. Subsequently, the solution is replaced with the best set of neighbors and shared solutions. Once all the solutions are improved by neighbor solutions, this procedure is repeated a number of times m (tours) after which the leader solution becomes the last one, and one of the other solutions with best value becomes leader and another loop starts. The algorithm terminates when the number of iterations reaches the limit.

The conceptual similarity between the parameters of the algorithm of MBO with the actual migration of birds in V-formation is studied in Duman et al. [7] and is summarized in Table 1.

Table 1. Similarities of MBO meta-heuristic and V-shape natural migration of birds.

Parameter of MBO	Parameter Description	Similar concept in real migration birds in V-formation.
n	The number of initial solutions of the flock.	Birds in V-formation.
k	The number of neighboring solutions generated for each initial solution.	The induced power required which is inversely proportional to the speed.
x	The number of neighboring solutions shared with the next solution.	Wing-Tip Spacing (WTS).
m	The number of tours.	The number of wing flaps before a change occurs in the leading bird.
K	The number of iterations (total number of generated neighbor solutions).	There is no conceptual relationship.

Below, first the notation used and then the pseudocode of the MBO algorithm are given.

Algorithm 1: Pseudocode of Migrating Birds Optimization

Generate n initial solutions in a random manner and place them on an hypothetical V-formation arbitrarily;
$i = 0$;
while $(i < K)$ **do**
    for $j = 0$ *to* $j < m$ **do**
        Try to improve the leading solution by generating and evaluating k neighbors of it (for the implementation of machine-part cell formation problem, a neighbor solution is obtained randomly by choosing a machine and reassigning it to a randomly chosen cell);
        $i = i + k$;
        for *each solution* S_r *in the flock (except leader)* **do**
            Try to improve S_r by evaluating $(k - x)$ neighbors of it and x unused best neighbors from the solution in the front;
            $i = i + (k - x)$;
        end
    end
    Move the leader solution to the end and forward one of the solutions following it to the leader position;
end
return the best solution in the flock;

5 Computational experiments

The MBO algorithms for machine-part cell formation was coded in Java SE-1.7 (Java SE 7, 1.7.0_55) and was run on a computer MacBook Pro (Retina, 13-inch, Late 2013) with an Intel Core i5 Processor 2.4 GHz, 4 GB RAM 1600 MHz DDR3 and Video Card Intel Iris 1536 MB running OS X Yosemite version 10.10.4. We have tested 90 problems (10 instances considerering 5 values of $Mmax$ for $C = 2$ (Cells) and 10 intances considering 4 values of $Mmax$ for $C = 3$, see Table 2 and Table 3).

Such 90 problems have been taken from Boctor's experiments [4] in order to compare it with previous work. To consider the parameters used by MBO, the best values reported by Duman et al. [7], $n = 51, k = 3, m = 10$ and $x = 1$. In addition to the K (iteration limit) setting a value of 1020 is assigned. Each experiment was executed 100 times.

Table 2 and Table 3 contrasts the optimun value reached by using different techniques for the 90 problems. Column 1 (Instance) corresponds to the identifier assigned to each instance, column 2 (Boctor Problem) represents the identifier

Table 2. Experiments using $C = 2$: Optimum values for Migrating Birds Optimization (MBO), Simulated Annealing (SA), and Particle Swarm Optimization (PSO).

Instance	Boctor Problem	Mmax	Optimum Value	MBO			SA	PSO
				Optimum	Average	RPD%	Optimum	Optimum
1	1	8	**11**	**11**	12.81	0.00	**11**	**11**
2	1	9	**11**	**11**	11.42	0.00	**11**	**11**
3	1	10	**11**	**11**	11.27	0.00	**11**	**11**
4	1	11	**11**	**11**	11.65	0.00	**11**	**11**
5	1	12	**11**	**11**	12.95	0.00	**11**	**11**
6	2	8	**7**	**7**	7.82	0.00	**7**	**7**
7	2	9	**6**	**6**	7.3	0.00	**6**	**6**
8	2	10	**4**	**4**	5.43	0.00	10	5
9	2	11	**3**	**3**	3.86	0.00	4	4
10	2	12	**3**	**3**	3.73	0.00	**3**	4
11	3	8	**4**	**4**	5.22	0.00	5	5
12	3	9	**4**	**4**	5.29	0.00	**4**	**4**
13	3	10	**4**	**4**	5.19	0.00	**4**	5
14	3	11	**3**	**3**	3.95	0.00	4	4
15	3	12	**1**	**1**	2.62	0.00	4	3
16	4	8	**14**	**14**	15.1	0.00	**14**	15
17	4	9	**13**	**13**	13.37	0.00	**13**	**13**
18	4	10	**13**	**13**	13.47	0.00	**13**	**13**
19	4	11	**13**	**13**	13.68	0.00	**13**	**13**
20	4	12	**13**	**13**	13.65	0.00	**13**	**13**
21	5	8	**9**	**9**	9.92	0.00	**9**	10
22	5	9	**6**	**6**	7.1	0.00	**6**	8
23	5	10	**6**	**6**	6.98	0.00	**6**	**6**
24	5	11	**5**	**5**	5.9	0.00	7	**5**
25	5	12	**4**	**4**	5.06	0.00	**4**	5
26	6	8	**5**	**5**	6.69	0.00	**5**	**5**
27	6	9	**3**	**3**	3.77	0.00	**3**	**3**
28	6	10	**3**	**3**	4.08	0.00	5	**3**
29	6	11	**3**	**3**	4.03	0.00	**3**	4
30	6	12	**2**	**2**	2.74	0.00	3	4
31	7	8	**7**	**7**	7.81	0.00	**7**	**7**
32	7	9	**4**	**4**	6.02	0.00	**4**	5
33	7	10	**4**	**4**	5.26	0.00	**4**	5
34	7	11	**4**	**4**	5.32	0.00	**4**	5
35	7	12	**4**	**4**	5.24	0.00	**4**	5
36	8	8	**13**	**13**	13.7	0.00	**13**	14
37	8	9	**10**	**10**	11.66	0.00	20	11
38	8	10	**8**	**8**	9.19	0.00	15	10
39	8	11	**5**	**5**	6.22	0.00	11	6
40	8	12	**5**	**5**	7	0.00	7	6
41	9	8	**8**	**8**	9.9	0.00	13	9
42	9	9	**8**	**8**	9.85	0.00	**8**	**8**
43	9	10	**8**	**8**	9.64	0.00	**8**	**8**
44	9	11	**5**	**5**	6.77	0.00	8	**5**
45	9	12	**5**	**5**	6.91	0.00	8	8
46	10	8	**8**	**8**	8.95	0.00	**8**	9
47	10	9	**5**	**5**	6.31	0.00	**5**	8
48	10	10	**5**	**5**	6.29	0.00	**5**	7
49	10	11	**5**	**5**	5.84	0.00	**5**	7
50	10	12	**5**	**5**	6.41	0.00	**5**	6

Table 3. Experiments using $C = 3$: Optimum values for Migrating Birds Optimization (MBO), Simulated Annealing (SA), and Particle Swarm Optimization (PSO).

Instance	Boctor Problem	Mmax	Optimum Value	MBO			SA	PSO
				Optimum	Average	RPD%	Optimum	Optimum
51	1	6	**27**	**27**	29.44	0.00	28	-
52	1	7	**18**	**18**	20.77	0.00	**18**	-
53	1	8	**11**	**11**	13.22	0.00	**11**	-
54	1	9	**11**	**11**	12.23	0.00	**11**	-
55	2	6	**7**	**7**	9.08	0.00	**7**	-
56	2	7	**6**	**6**	7.42	0.00	**6**	-
57	2	8	**6**	**6**	7.01	0.00	7	-
58	2	9	**6**	**6**	7.33	0.00	**6**	-
59	3	6	**9**	**9**	10.08	0.00	12	-
60	3	7	**4**	**4**	6.67	0.00	8	-
61	3	8	**4**	**4**	5.51	0.00	8	-
62	3	9	**4**	**4**	4.84	0.00	**4**	-
63	4	6	**27**	**27**	28.03	0.00	**27**	-
64	4	7	**18**	**18**	20	0.00	**18**	-
65	4	8	**14**	**14**	15.71	0.00	**14**	-
66	4	9	**13**	**13**	14.42	0.00	**13**	-
67	5	6	**11**	**11**	12.29	0.00	**11**	-
68	5	7	**8**	**8**	9.55	0.00	9	-
69	5	8	**8**	**8**	9.53	0.00	9	-
70	5	9	**6**	**6**	7.82	0.00	8	-
71	6	6	**6**	**6**	6.97	0.00	8	-
72	6	7	**4**	**4**	5.72	0.00	5	-
73	6	8	**4**	**4**	5.39	0.00	5	-
74	6	9	**3**	**3**	4.64	0.00	4	-
75	7	6	**11**	**11**	13.21	0.00	**11**	-
76	7	7	**5**	**5**	6.37	0.00	**5**	-
77	7	8	**5**	**5**	7.1	0.00	**5**	-
78	7	9	**4**	**4**	6.35	0.00	5	-
79	8	6	**14**	**14**	15.11	0.00	**14**	-
80	8	7	**11**	**11**	12.71	0.00	**11**	-
81	8	8	**11**	**11**	13.23	0.00	**11**	-
82	8	9	**10**	**10**	11.69	0.00	**10**	-
83	9	6	**12**	**12**	14.39	0.00	**12**	-
84	9	7	**12**	**12**	13.42	0.00	**12**	-
85	9	8	**8**	**8**	10.73	0.00	13	-
86	9	9	**8**	**8**	9.68	0.00	**8**	-
87	10	6	**10**	**10**	13	0.00	12	-
88	10	7	**8**	**8**	9.32	0.00	14	-
89	10	8	**8**	**8**	9.14	0.00	**8**	-
90	10	9	**5**	**5**	7.45	0.00	8	-

Table 4. Number of optimal values reached.

Meta-heuristic	C = 2					C = 3			
	M8	M9	M10	M11	M12	M6	M7	M8	M9
MBO	10	10	10	10	10	10	10	10	10
SA	8	9	7	5	6	6	6	5	6
PSO	4	6	5	4	2	-	-	-	-

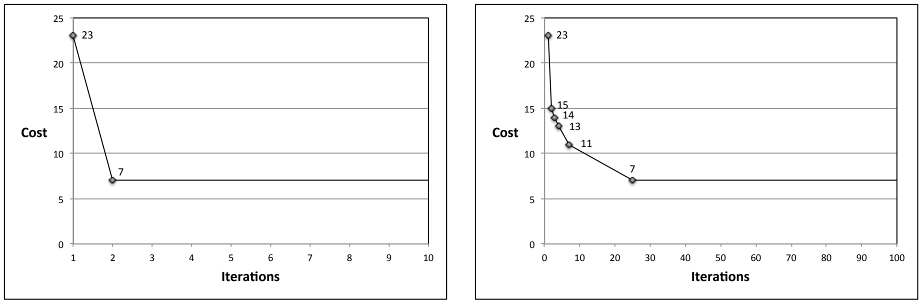

Fig. 5. Convergence chart for Instance 55.

of the 10 Boctor problems [4], column 3 (Mmax) corresponds to the maximum number of machines per cell, column 4 (Optimum Value) depicts the optimum value for the given problem, column 5 (MBO-Optimum) the best value reached by using Migrating Birds Optimization, column 6 (MBO-Average) the average value of 100 executiones is depicted, column 7 (MBO-RPD%) represents the difference between the best known optimun value and the best optimum value reached by MBO in terms of percentage, column 8 (SA-Optimum) the best value using Simulated Annealing [4,29], and column 9 (PSO-Optimum) the optimun value using Particle Swarm Optimization [9,8].

As can be observed (see Table 2 and Table 3), the algorithm MBO able to find an optimal solution to all problems and takes the first place. Table 4 summarizes the optimal amount that have reached MBO, SA and PSO for each instance of Boctor's problem. The experimental results shows that the proposed MBO provides high quality solutions and good performance within 2 and 3 cells reaching RPD% = 0 for all tested instances. Fig. 5 shows the graph of convergence for instance number 55 (Boctor Problem 2 solved by MBO with $C = 3$, $Mmax = 6$ and Optimum value = 7). MBO has a rapid convergence (left graph in Figure 5), this is because employing a mechanism neighboring solutions shared with the next solution. Therefore, the algorithm MBO found the optimum value for the instance 55 in the iteration number 2. For a more detailed view of the convergence of the algorithm MBO, a modification of pseudocode MBO was developed ignoring lines 6 and 9, subsequently increased iteration after line 12 was implemented. The results of these changes can be seen in Figure 5 (see chart right) with the best evaluations of the objective function (see equation 1).

6 Conclusions

In this paper, a new approach for machine-part cell formation problem based on migrating birds optimization has been proposed. The result obtained in the computational experiences carried out show that proposed algorithm can generate optimal. The comparisons between MBO and other metaheuristics indicates that our algorithm is a better algorithm for solving machine-part cell formation problem. Indeed, the global optimum was reached in all instances. This is because MBO has a rapid convergence, mainly because it uses a mechanism to share neighboring solutions to the next solution. In future steps, the algorithm will be applicate to a variety with larger problems. In addition, parameter optimization and other approaches are also topics for future research.

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References

1. Alkaya, A.F., Algin, R.: Metaheuristic based solution approaches for the obstacle neutralization problem. Expert Systems with Applications 42(3), 1094–1105 (2015)
2. Badgerow, J.P., Hainsworth, F.R.: Energy savings through formation flight? a reexamination of the vee formation. Journal of Theoretical Biology 93(1), 41–52 (1981)
3. Bajec, I.L., Heppner, F.H.: Organized flight in birds. Animal Behaviour 78(4), 777–789 (2009)
4. Boctor, F.: A linear formulation of the machine-part cell formation problem. International Journal Production Research 29(2), 343–356 (1991)
5. Burbidge, J.L.: Production flow analysis. Production Engineer 42(12), 742–752 (December 1963)
6. Crawford, B., Soto, R., Zuñiga, G., Monfroy, E., Paredes, F.: Modeling manufacturing cell design problems: Cp vs. mh. In: HCI International 2014-Posters Extended Abstracts, pp. 498–502. Springer (2014)
7. Duman, E., Uysal, M., Alkaya, A.F.: Migrating birds optimization: A new metaheuristic approach and its performance on quadratic assignment problem. Information Sciences 217, 65–77 (2012)
8. Duran, O., Rodriguez, N., Consalter, L.A.: Hybridization of pso and a discrete position update scheme techniques for manufacturing cell design. In: MICAI 2008: Advances in Artificial Intelligence, pp. 503–512. Springer (2008)
9. Durán, O., Rodriguez, N., Consalter, L.A.: Collaborative particle swarm optimization with a data mining technique for manufacturing cell design. Expert Systems with Applications 37(2), 1563–1567 (2010)
10. Gunasingh, K.R., Lashkari, R.: Simultaneous grouping of parts and machines in cellular manufacturing systemsan integer programming approach. Computers & industrial engineering 20(1), 111–117 (1991)
11. Hummel, D., Beukenberg, M.: Aerodynamische interferenzeffekte beim formationsflug von vögeln. Journal für Ornithologie 130(1), 15–24 (1989)
12. Joines, J.A., Kay, M.G., King, R.E., Thomas Culbreth, C.: A hybrid genetic algorithm for manufacturing cell design. Journal of the Chinese Institute of Industrial Engineers 17(5), 549–564 (2000)

13. Kusiak, A.: The part families problem in flexible manufacturing systems. Annals of Operations Research 3(6), 277–300 (1985)
14. Li, X., Baki, M., Aneja, Y.P.: An ant colony optimization metaheuristic for machine–part cell formation problems. Computers & Operations Research 37(12), 2071–2081 (2010)
15. Lissaman, P., Shollenberger, C.A.: Formation flight of birds. Science 168(3934), 1003–1005 (1970)
16. Lozano, S., Adenso-Diaz, B., Eguia, I., Onieva, L., et al.: A one-step tabu search algorithm for manufacturing cell design. Journal of the Operational Research Society 50(5), 509–516 (1999)
17. Mosier, C., Taube, L.: The facets of group technology and their impacts on implementationa state-of-the-art survey. Omega 13(5), 381–391 (1985)
18. Niroomand, S., Hadi-Vencheh, A., Şahin, R., Vizvari, B.: Modified migrating birds optimization algorithm for closed loop layout with exact distances in flexible manufacturing systems. Expert Systems with Applications (2015)
19. Pan, Q.K., Dong, Y.: An improved migrating birds optimisation for a hybrid flowshop scheduling with total flowtime minimisation. Information Sciences 277, 643–655 (2014)
20. Purcheck, G.F.K.: A linear–programming method for the combinatorial grouping of an incomplete power set. Journal of Cybernetics 5(4), 51–76 (1975)
21. Rayner, J.: A new approach to animal flight mechanics. Journal of Experimental Biology 80(1), 17–54 (1979)
22. Seifoddini, H., Hsu, C.P.: Comparative study of similarity coefficients and clustering algorithms in cellular manufacturing. Journal of Manufacturing Systems 13(2), 119–127 (1994)
23. Selim, H., Askin, R., Vakharia, A.: Cell formation in group technology: review, evaluation and directions for future research. Computers and Industrial Engineering 34(1), 3–20 (January 1998)
24. Shafer, S.M., Rogers, D.F.: A goal programming approach to the cell formation problem. Journal of Operations Management 10(1), 28–43 (1991)
25. Soto, R., Kjellerstrand, H., Durán, O., Crawford, B., Monfroy, E., Paredes, F.: Cell formation in group technology using constraint programming and boolean satisfiability. Expert Systems with Applications 39(13), 11423–11427 (2012)
26. Soto, R., Kjellerstrand, H., Gutiérrez, J., López, A., Crawford, B., Monfroy, E.: Solving manufacturing cell design problems using constraint programming. In: Advanced Research in Applied Artificial Intelligence, pp. 400–406. Springer (2012)
27. Venugopal, V., Narendran, T.: A genetic algorithm approach to the machine-component grouping problem with multiple objectives. Computers & Industrial Engineering 22(4), 469–480 (1992)
28. Wu, T.H., Low, C., Wu, W.T.: A tabu search approach to the cell formation problem. The International Journal of Advanced Manufacturing Technology 23(11-12), 916–924 (2004)
29. Wu, T.H., Chang, C.C., Chung, S.H.: A simulated annealing algorithm for manufacturing cell formation problems. Expert Systems with Applications 34(3), 1609–1617 (2008)