



# CARIMO - A heuristic approach to machine-part cell formation

RAJESH PICHANDI<sup>1</sup>, N SRINIVASA GUPTA<sup>1\*</sup> and CHANDRASEKHARAN RAJENDRAN<sup>2</sup>

<sup>1</sup>School of Mechanical Engineering, Vellore Institute of Technology (VIT), Vellore, Tamil Nadu, India

<sup>2</sup>Department of Management Studies, Indian Institute of Technology Madras, Chennai, India  
e-mail: srinivasagupta.n@vit.ac.in

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**Abstract.** This paper presents a correlation analysis-based heuristic for the machine-part cell formation in the context of cellular manufacturing systems. Two new indices, viz. “*mean correlation index*” for forming the part families and “*relevance index-modified*” for identifying the appropriate machine cells are proposed. The machine-part cells formed by the proposed heuristic resulted in a higher grouping efficacy (GE) for 14.3% of the test instances gathered from the literature, and it performed equal to the best in class heuristics available in the literature for 80% of the test instances. The method presented in this paper has set a new benchmark GE for 5 of the 35 test instances used by the researchers in the context of machine-part cell formation without singletons.

**Keywords.** Manufacturing systems; cellular manufacturing system; machine cell; part family; grouping efficacy; correlation analysis-based heuristic.

## 1. Introduction

In the present era of consumer-centric markets, attracting customers and retaining them are two significant challenges for the manufacturer. Most customers demand a variety of customized products, and they expect quick delivery. This concern has been well addressed by cellular manufacturing systems (CMS) that aim at manufacturing near similar products in mid-volume in a cellular layout. Manufacturing companies that have implemented a cellular layout have reported a reduction in material handling cost and production lead time [1]. The companies that are manufacturing in batches can significantly reduce material handling costs and the ratio of machine operating time to machine setup time by changing from a batch layout to cellular layout. Machine-part cell formation (MPCF) is one of the fundamental tasks in CMS design and involves part family (PF) formation and machine cell (MC) identification [2]. From the total number of parts manufactured by the company, part families are formed by grouping the near similar parts. From the available machines, the most relevant machines are grouped for each of the part families, and they are arranged in cells. Identification of the part families and the machine cells are mathematically categorized as NP-complete [3].

MPCF starts with the input in the form of a matrix with machines in rows and parts in columns. The intersection point of each machine and part is represented as 0 or 1. If the part does not require the machine for its production, then it is denoted as 0. If the part requires the machine for

its production, then it is denoted as 1. This matrix is called the machine-part incidence matrix (MPIM). In the MPCF, the part families and machine cells are formed in a way that will minimize the intercellular movement of parts and maximize the utilization of machines.

Researchers have attempted to solve the MPCF in three different ways:

1. Part grouping followed by machine cell creation
2. Machine grouping followed by part family creation
3. Simultaneous grouping of parts and machines

The following clustering methods developed in the early stage of CMS. McAuley [4] used the single linkage clustering (SLC) procedure with the Jaccard coefficient as a similarity measure. McCormick *et al* [5] developed the bond energy algorithm (BEA). Ei-Essawy and Torrance [6] proposed component flow analysis (CFA). Rajagopalan and Batra [7] proposed a graph-theoretic approach. King [8] developed the rank order clustering (ROC), an array sorting procedure for MPCF. Seifoddini and Wolfe [9] used the average linkage clustering (ALC) to overcome the chaining issue observed while using the single-linkage clustering (SLC). However, Gupta and Seifoddini [10] concluded that complete Linkage clustering (CLC) suffers the least with the chaining effect.

Chandrasekharan and Rajagopalan [11] proposed an algorithm that formulates the given problem as a bipartite graph to get the insights on its connectivity, and the results are used as the seed for a non-hierarchical clustering procedure to get the machine-part cells. They proposed the first-ever quantitative measure called grouping efficiency to evaluate the goodness of different solutions to the given problem. Chandrasekharan and

\*For correspondence  
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Rajagopalan [12] developed an extended version of the ideal seed algorithm for the concurrent formation of machine-part cells, which is popularly known as zero-one data ideal seed algorithm for clustering (ZODIAC). Ballakur and Steudel [3] proposed a heuristic based on dynamic programming (DP) and introduced a new measure known as cell bond strength to find the best chain of machines/parts.

Seifoddini [13] proposed the reassignment of the bottleneck machines to appropriate cells to reduce the number of inter-cellular moves. Wei and Gaiher [14] developed a linear integer programming (LIP) approach to minimize bottleneck cost, to improve the average cell utilization, and to minimize intracell and inter-cell load imbalances. Askin *et al* [15] solved the MPCF by formulating the problem as a Hamiltonian path problem. Srinivasan and Narendran [16] proposed a non-hierarchical clustering algorithm GRAFICS, which starts with solving the given MPIM as an assignment problem to get the initial machine cells. The initial machine cells are treated as seeds to cluster the parts. Boctor [17] used a mixed-integer linear program (MILP) approach to minimize the exceptional elements. Ribeiro and Pradin [18] used a partitioning and reassigning method to reduce inter-cell movements. Srinivasan [19] proposed an approach to MPCF using a minimum spanning tree (MST). Lin *et al* [20] solved the machine cell imbalance problem using a weighted minimum spanning tree method. Won and Kim [21] proposed a multiple criteria clustering algorithm to solve the MPCF problem with multiple process routings using a generalized machine similarity coefficient. Cheng *et al* [22] formulated the MPCF as a traveling salesman problem and solved it using a genetic algorithm (referred to as GA-TSP). Won [23] used an efficient p-median algorithm and maximum density rule to minimize the exceptional elements.

Dimopoulos and Mort [24] introduced the genetic programming (GP) approach to MPCF, but the computation time was high due to the requirement of recalculation of the similarity matrix for all iterations. Onwubolu and Mutingi [25] grouped the part family and machine cells simultaneously to reduce intercellular movements using a genetic algorithm (referred to as GA1). Goncalves and Resende [26] used a local search heuristic with a GA (referred to as GA2) for the MPCF problem.

Gupta *et al* [27] introduced a correlation analysis and relevance index (CARI) based approach for the MPCF problem. Pradhan and Mishra [28] proposed a part family creation procedure using a self-organizing map (SOM). However, their method required manual rearrangement of bottleneck machines. Elbenani and Ferland [29] proposed a solution procedure that reduced the fractional programming cell formation problem to several integer linear programming (ILP) problems using the Dinkelbach procedure and solved each ILP using CPLEX solver. Brusco [30] used a branch and bound algorithm to solve the MPCF problem. However, all these approaches solved the MPCF for a fixed number of cells. Later, Utkina *et al* [31] used a branch and bound algorithm for MPCF with a variable number of cells. They reported a higher GE for 21 of 35 benchmark test instances.

Subsequently, Utkina *et al* [32] reported a higher GE for 24 of 35 benchmark test instances by using the Dinkelbach procedure. In both these papers, they compared their results with the solutions achieved by Bychkov *et al* [33] in which a branch bound procedure was used with a variable number of cells. However, the machine-part cells formed by their procedure contained singletons. By definition, a singleton cell has either one machine with several parts or vice versa. Bychkov and Batsyn [34] solved the MPCF problem with a variable number of cells. However, those methods allow the formation of singleton cells. Chandrasekharan and Rajagopalan [11] emphasized that the non-singleton clusters are natural clusters, and the clusters formed with singletons are unnatural. Nair and Narendran [35] iterated that the singleton or single element clusters are an obstacle for the MPCF, and they suggested that the non-singleton block diagonal matrix is the proper block diagonal matrix. Won and Currie [36] also argued that if the MPCF has a singleton or empty part families/machine cells, then it is an improper block diagonal matrix. Farahani and Hosseini [37] observed that the non-singleton clusters result in high-quality solutions, whereas the singleton clusters can degrade the quality of results.

Octavio *et al* [38] provide a comparative study on the use of metaheuristic procedures for solving computationally hard problems including the MPCF problem and concluded that the performance of genetic algorithm with group-based representation is better than the particle swarm optimization with machine-based encoding. Shashikumar *et al* [39] proposed an integrated approach combining the power of a heuristic for domain selection, genetic algorithm for machine cell formation and a membership index for assigning parts to machine cells. Sharma *et al* [40] investigated 17 essential factors and concluded that human-related factors are dominant in implementing a cellular manufacturing system followed by operational factors, structural factors and process improvement factors. Kamalakannan *et al* [41] used simulated annealing with a perturbation scheme for solving the MPCF with ratio level data. Dmytryshyn *et al* [42] suggested a progressive modeling; a component-based optimization technique and proposed a solution representation that eliminates the need for encoding and decoding operations of metaheuristic procedures. Mourtzis *et al* [43] proposed an adaptive scheduling algorithm that can be used in manufacturing cells for enabling real-time cooperation among the operations manager, machines and operators.

Danilovic and Ilic [44] proposed an algorithm to solve complex and multi criteria MPCF problems, in which the unique details of the input instances were used to narrow down the feasible set and thus improving the solution efficiency. Ulutas [45] proposed an immune system based clonal selection algorithm (CSA) with encoding structure to solve the real sized problems.

In accordance with the majority of the researches including Gupta and Seifoddini [10], Chandrasekharan and Rajagopalan [11], Chandrasekharan and Rajagopalan [12], Srinivasan and Narendran [16], Boctor [17], Dimopoulos and Mort [24],

Goncalves and Resende [26], Farahani and Hosseini [37], Mosier and Taube [46], Srinivasan *et al* [47], Paydar and Saidi-Mehrabad [48], who observed and emphasized that the MPCF procedures should find the non-singleton clusters for achieving high-quality results, the heuristic described in this paper finds non-singleton machine-part cells using correlation analysis (CA) for identifying the part families and a relevance index-modified (RIMO) for finding the most appropriate machine cell for each part family. Putting the two measures together, i.e., correlation analysis and relevance index-modified, the heuristic presented in this paper is named as CARIMO heuristic. The CARIMO heuristic has achieved a higher GE than the GA2 algorithm and CARI heuristic for 14.3% and 31.4% of the standard test instances, respectively.

### 1.1 Highlights and contributions

The CARIMO heuristic has set a new benchmark GE value for the test instances 21, 29, 30, 33 and 34. To the best of our knowledge, among the heuristic and meta-heuristic approaches that produce non-singleton machine part cells, the CARIMO heuristic has achieved a higher GE for 5 out of 35 test instances and achieved equal to the best GE found in the literature for the remaining 28 out of 35 test instances. The improvement in GE ranges from 0.14% (for the dataset 21) to 1.73% (for the dataset 29). Even though the percentage of GE improvement appears to be small, the impact of such improvement on the material handling cost is significant.

Megala *et al* [49] explained the economic benefits of improvement in GE value and they claim that even the improvement of GE by 1% can have huge cost savings due to the reduced intercellular movements. Askin and Subramanian [50] and Choi and Cho [51] are also in support of the fact that even a small improvement in GE can have a huge positive impact on the manufacturing cost. Since the CARIMO heuristic is developed to find the non-singleton clusters, it is not compared with the methods proposed by Elbenani and Ferland [29], Brusco [30], Utkina *et al* [31] and Utkina *et al* [32] due to the presence of singleton clusters in their MPCF solutions.

## 2. Problem definition

The CARIMO heuristic finds non-singleton machine-part cells to minimize the intercellular movement of parts and maximize the utilization of machines in each cell. GE measure proposed by Kumar and Chandrasekharan [52] is used in this paper to assess the quality of machine-part cells. Equation (1) gives the formula for calculating GE.

$$GE = \frac{(N_1 - N_1^{out})}{(N_1 + N_0^{in})} \quad (1)$$

where

$N_1$  - Total number of 1's in the MPIM

$N_1^{out}$  - Total number of 1's outside the diagonal blocks (Exceptional Elements)

$N_0^{in}$  - Total number of 0's inside the diagonal blocks (Voids)

Goncalves and Resende [26] provide the justification for using the GE measure. They insisted that GE is a robust measure to report the quality of the MPCF solutions as it captures the voids as well as exceptional elements, and it can differentiate between the well-structured and ill-structured MPIM.

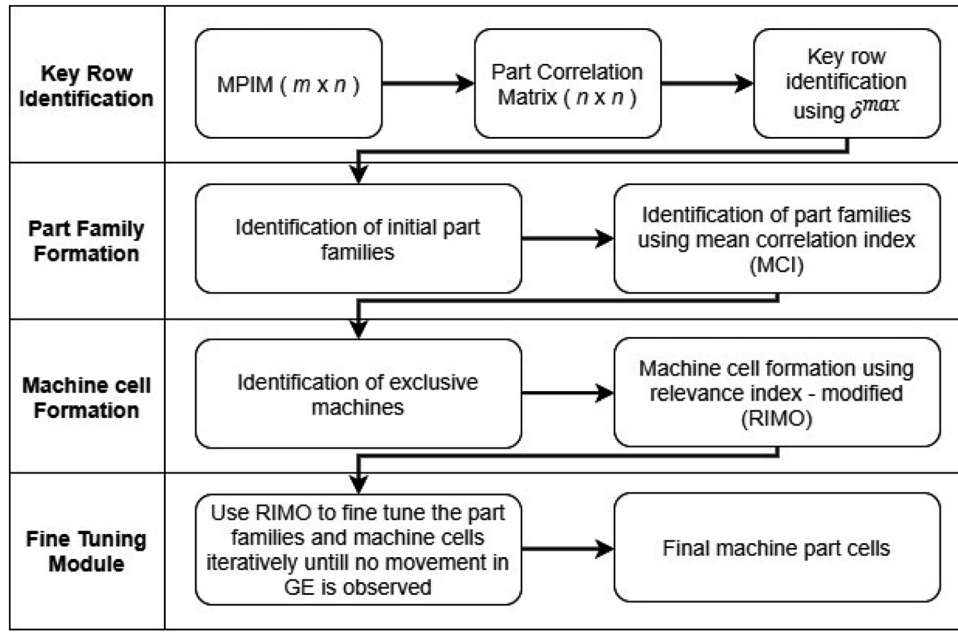
Paydar and Saidi-Mehrabad [48] observed that GE is an independent measure, and it is not affected by the number of cells. Al-Bashir *et al* [53] developed a weighted modified grouping efficacy measure. However, this measure does not consider the number of voids, and hence it can lead to higher GE. Majority of the researchers including Gupta and Seifoddini [10], Chandrasekharan and Rajagopalan [11], Chandrasekharan and Rajagopalan [12], Srinivasan and Narendran [16], Boctor [17], Dimopoulos and Mort [24], Goncalves and Resende [26], Gupta *et al* [27], Brusco [30], Utkina *et al* [32], Bychkov *et al* [33], Bychkov and Batsyn [34], Farahani and Hosseini [37], Mosier and Taube [46], Srinivasan *et al* [47], Paydar and Saidi-Mehrabad [48], Waghodekar and Sahu [54] used the GE measure to assess the quality of the machine-part cells. Hence the GE measure shown in equation (1) is used in this paper for assessing the quality of the MPCF solution.

## 3. CARIMO heuristic- The proposed approach

The CARIMO heuristic has four stages. In the first stage, the key row is identified for getting the respective initial part families. Part families are formed in the second stage using the *mean correlation index* (MCI). *RIMO* index is used to create the machine cells in the third stage, and a fine-tuning module is used in the fourth stage to place the weakly correlated members of each group into the most appropriate group. Figure 1 shows the flow chart of the CARIMO heuristic.

### 3.1 Identification of the key row of the part correlation matrix

From the MPIM of size  $(m \times n)$  with  $m$  machines and  $n$  parts, the part correlation matrix (PCM) of size  $(n \times n)$  is formed with diagonal elements equal to 1 representing the correlation coefficient of a part and itself. The  $(i, j)^{th}$  element in the PCM represents the correlation coefficient of the  $i^{th}$  and  $j^{th}$  parts. The correlation coefficient ( $S_{ij}$ ) serves as a measure of similarity, which is calculated using the equation (2):



**Figure 1.** Flow chart of the CARIMO heuristic.

$$S_{ij} = \frac{n \sum ij - \sum i \sum j}{\sqrt{\left(n \sum i^2 - \left(\sum i\right)^2\right) \left(n \sum j^2 - \left(\sum j\right)^2\right)}} \quad (2)$$

$S_{ij}$  value varies from  $-1$  to  $+1$ . The  $S_{ij}$  value  $-1$  indicates a perfect negative linear relationship;  $S_{ij}$  value  $+1$  indicates a perfect positive linear relationship, and  $S_{ij}$  value  $0$  indicates that there is no relationship between the pair of parts. In this paper, the PCM is formed using the *corrcoeff* function in the MATLAB software.

Identification of the key row of the PCM for initiating the part family helps to form the initial part families that results in the final part families that contain highly correlated parts in them, and also it helps to reach the final solution quickly.  $\delta$  is the difference between the maximum and minimum correlation value for each row of the PCM, and the higher value among them is  $\delta^{max}$ .  $\delta^{max}$  is used to find the key row of the PCM.  $\delta$  is calculated using equation (3):

$$\{\delta\}_{i=1}^{i=n} = \{\max(S_{ij}) - \min(S_{ij})\}_{j=1}^{j=n} \quad (3)$$

where

$S_{ij}$  = Correlation coefficient.

Initial part families are identified from the key row by finding the pair(s) of parts with the maximum correlation and the pair(s) of parts with minimum correlation. The first initial part family (PF1<sup>●</sup>) consists of the pair(s) of parts

with the maximum correlation. The second initial part family (PF2<sup>●</sup>) consists of the part(s) that has the minimum correlation.

The remaining parts that are not part of PF1<sup>●</sup> and PF2<sup>●</sup> are declared as doubt elements (DE). Consider the MPIM of size  $(8 \times 12)$ , i.e., eight machines (M1 to M8) and 12 parts (P1 to P12), shown in table 1. The PCM of the MPIM, which is formed using the *corrcoeff* function in the MATLAB software is shown in table 2. Figure 2 gives the steps involved in calculating the correlation coefficient.

The  $(\delta)$  of each row of the PCM is shown in table 3. Based on the  $\delta^{max}$  value, the third row of the PCM is identified as the key row. In the key row, P4 has the highest correlation ( $S_{ij} = 1$ ) with P3; P11 has the least correlation ( $S_{ij} = -0.60$ ) with P3. Hence, PF1<sup>●</sup> is formed with P3 and P4 as members, and PF2<sup>●</sup> is formed with P11 as a member. The remaining parts are declared as DE.

PF1<sup>●</sup>  $\rightarrow$  {P3, P4}

PF2<sup>●</sup>  $\rightarrow$  {P11}

DE  $\rightarrow$  {P1, P2, P5, P6, P7, P8, P9, P10, P12}.

### 3.2 Mean correlation index (MCI)

In this paper, the *mean correlation index* (MCI) is proposed for finding the appropriate part family for the parts in DE. MCI is used to find the appropriate PF for part  $x$  in DE:

$$MCI = \frac{\{(S_{xa} - \theta)(S_{xb} - \theta) + \dots + (S_{xn} - \theta)\}}{n} \quad (4)$$

where

**Table 1.** Machine-Part Incidence Matrix ( $8 \times 12$ ).

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
M1	1	1	1	1	0	0	0	0	0	0	0	0
M2	1	0	1	1	1	1	1	0	0	1	0	0
M3	0	0	1	1	1	1	1	1	1	0	0	0
M4	0	0	0	0	0	1	1	1	1	1	0	0
M5	0	0	0	0	0	0	1	1	1	1	0	0
M6	0	0	0	0	0	0	1	1	1	0	1	0
M7	0	0	0	0	0	0	0	0	0	0	1	1
M8	0	0	0	0	0	0	0	0	0	0	1	1

**Table 2.** Part correlation matrix of MPIM.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
P1	1.00	0.65	0.75	0.75	0.33	0.15	−0.15	−0.58	−0.58	0.15	−0.45	−0.33
P2	0.65	1.00	0.49	0.49	−0.22	−0.29	−0.49	−0.38	−0.38	−0.29	−0.29	−0.22
P3	0.75	0.49	1.00	1.00	0.75	0.47	0.07	−0.26	−0.26	−0.07	−0.60	−0.45
P4	0.75	0.49	1.00	1.00	0.75	0.47	0.07	−0.26	−0.26	−0.07	−0.60	−0.45
P5	0.33	−0.22	0.75	0.75	1.00	0.75	0.45	0.00	0.00	0.15	−0.45	−0.33
P6	0.15	−0.29	0.47	0.47	0.75	1.00	0.60	0.26	0.26	0.47	−0.60	−0.45
P7	−0.15	−0.49	0.07	0.07	0.45	0.60	1.00	0.77	0.77	0.60	−0.47	−0.75
P8	−0.58	−0.38	−0.26	−0.26	0.00	0.26	0.77	1.00	1.00	0.26	−0.26	−0.58
P9	−0.58	−0.38	−0.26	−0.26	0.00	0.26	0.77	1.00	1.00	0.26	−0.26	−0.58
P10	0.15	−0.29	−0.07	−0.07	0.15	0.47	0.60	0.26	0.26	1.00	−0.60	−0.45
P11	−0.45	−0.29	−0.60	−0.60	−0.45	−0.60	−0.47	−0.26	−0.26	−0.60	1.00	0.75
P12	−0.33	−0.22	−0.45	−0.45	−0.33	−0.45	−0.75	−0.58	−0.58	−0.45	0.75	1.00

**Step 1**

Choose the two vectors  $i$  and  $j$ , whose correlation coefficient is to be calculated.

**Step 2**

Use the following equation to calculate the correlation coefficient ( $S_{ij}$ ).

$$S_{ij} = \frac{n \sum ij - \sum i \sum j}{\sqrt{(n \sum i^2 - (\sum i)^2) (n \sum j^2 - (\sum j)^2)}}$$

For the purpose of sample calculation, P1 ( $i^{\text{th}}$  vector) and P2 ( $j^{\text{th}}$  vector) from the MPIM given in the table 1 are chosen. The values are calculated as shown in the following table and substituted in the equation.

	i (P1)	j (P2)	ij	i <sup>2</sup>	j <sup>2</sup>
M1	1	1	1	1	1
M2	1	0	0	1	0
M3	0	0	0	0	0
M4	0	0	0	0	0
M5	0	0	0	0	0
M6	0	0	0	0	0
M7	0	0	0	0	0
M8	0	0	0	0	0
$\Sigma$	2	1	1	2	1

Since the correlation coefficient of P1 and P2 is calculated with respect to their machining instances, the  $n$  value is 8, denoting the eight possible machining instances.

$$S_{ij} = \frac{(8 \times 1) - (2 \times 1)}{\sqrt{((8 \times 2) - 2^2)((8 \times 1) - 1^2)}} = 0.65$$

$S_{xa}$  – Correlation coefficient of part  $x$  in DE and Part  $a$  of the initial PF

$S_{xb}$  – Correlation coefficient of part  $x$  in DE and Part  $b$  of the initial PF

$S_{xn}$  – Correlation coefficient of part  $x$  in DE and Part  $n$  of the initial PF

$\theta$  – A variable, whose value varies from 0.05 to 0.6, in the increment of 0.05

$n$  – Number of parts in the part family (this value gets updated dynamically because a new part is added to a part family in successive iterations)

Based on its MCI value, a part in DE may find its place in any of the available part families or a new part family may be created. A positive MCI of a part in DE with a part family indicates that it is appropriate to place it in that part family. If a part has positive MCI for all the available part families, it will be placed in the part family with which it has the maximum positive MCI. In case of a tie, the part can be placed arbitrarily in any of the available part families. If a part has negative MCI for all the available part families, then a new part family is created with that part as the first member.

**Figure 2.** Calculation procedure for finding the correlation coefficient ( $S_{ij}$ ).



**Table 3.** Part correlation matrix with  $\delta$  value.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	Max	Min	( $\delta$ )
P1	-	0.65	0.75	0.75	0.33	0.15	-0.15	-0.58	-0.58	0.15	-0.45	-0.33	0.75	-0.58	1.33
P2	0.65	-	0.49	0.49	-0.22	-0.29	-0.49	-0.38	-0.38	-0.29	-0.29	-0.22	0.65	-0.49	1.14
P3 <sup>#</sup>	0.75	0.49	-	1	0.75	0.47	0.07	-0.26	-0.26	-0.07	-0.6	-0.45	1	-0.6	1.6 <sup>•</sup>
P4	0.75	0.49	1	-	0.75	0.47	0.07	-0.26	-0.26	-0.07	-0.6	-0.45	1	-0.6	1.6
P5	0.33	-0.22	0.75	0.75	-	0.75	0.45	0	0	0.15	-0.45	-0.33	0.75	-0.45	1.2
P6	0.15	-0.29	0.47	0.47	0.75	-	0.6	0.26	0.26	0.47	-0.6	-0.45	0.75	-0.6	1.35
P7	-0.15	-0.49	0.07	0.07	0.45	0.6	-	0.77	0.77	0.6	-0.47	-0.75	0.77	-0.75	1.52
P8	-0.58	-0.38	-0.26	-0.26	0	0.26	0.77	-	1	0.26	-0.26	-0.58	1	-0.58	1.58
P9	-0.58	-0.38	-0.26	-0.26	0	0.26	0.77	1	-	0.26	-0.26	-0.58	1	-0.58	1.58
P10	0.15	-0.29	-0.07	-0.07	0.15	0.47	0.6	0.26	0.26	-	-0.6	-0.45	0.6	-0.6	1.2
P11	-0.45	-0.29	-0.6	-0.6	-0.45	-0.6	-0.47	-0.26	-0.26	-0.6	-	0.75	0.75	-0.6	1.35
P12	-0.33	-0.22	-0.45	-0.45	-0.33	-0.45	-0.75	-0.58	-0.58	-0.45	0.75	-	0.75	-0.75	1.5

# - Key row; • -  $\delta^{max}$ .

**3.2a Rationale for using  $\theta$  and  $n$  in the MCI measure:** The presence of highly correlated parts in the PF results in the creation of a minimum number of exceptional elements, and a minimum number of voids. Thus, when a part in DE is tested for getting placed in any of the existing part families, the numerical measure used should be in a position to clearly indicate whether the entry of a new part in a PF will be advantageous for achieving a higher GE or not. The cumulative correlation index (CCI) proposed in Gupta *et al* [27] does not consider the number of parts in the part family being considered. However, the MCI proposed in this paper considers the number of parts ( $n$ ) and  $\theta$ . This procedure helps in finding the most appropriate part family for each part in DE. It should be noted that if simply the sum of the correlation coefficient of the part in the DE and the parts in the initial part families is calculated, there is a possibility for nullification of the total value, resulting in the wrong conclusion. The factor  $\theta$  is subtracted from the correlation coefficient to avoid the possible wrong conclusion.

For example, assume an initial PF consisting of two parts whose correlation coefficient is  $-0.9$  and  $+0.9$  with one of the parts in DE. If  $\theta$  is not subtracted and simply the sum is calculated, the net output will be zero. On the other hand, if  $\theta = 0.5$  is subtracted from the correlation coefficient values, then the sum will be  $-1$ .

This gives the inference that the part in DE should not be added to that PF. It should be noted that  $\theta$  value varies from 0.05 to 0.6 in the increment of 0.05 while calculating the MCI. Dividing the sum of  $S-\theta$  by the number of parts in the PF, helps in identifying the appropriate PF for the part in DE, whenever there is a tie in the sum of  $S-\theta$  or the sum of  $S-\theta$  values are very close. For example, consider a PF with 4 parts in it, and the sum of  $S-\theta$  of a part  $P_x$  in DE with this PF is equal to 1, and another PF with three parts in it and the sum of  $S-\theta$  of  $P_x$  with this PF is also equal to 1. Since the sum of  $S-\theta$  is equal to 1 for both the PF, if the PF with four parts is chosen, it will result in creating more exceptional elements (EE) and subsequently more voids (V). Dividing the sum of  $S-\theta$  by the total number of parts in it

results in 0.25 for the PF with four parts and 0.33 for the PF with three parts. Thus, part  $P_x$  is assigned to the PF with 3 parts in it. If the sum of  $S-\theta$  is not divided by the total number of parts, there is a possibility of choosing the wrong PF resulting in more exceptional elements and subsequently more voids.

**3.2b PF identification using MCI:** Consider the part P1 in DE. MCI of P1, if it is to be included with PF1, is defined as follows:

$$MCI_{P1} \text{ with PF1} = \{(S_{(1)(3)} - \theta) + (S_{(1)(4)} - \theta)\}/2,$$

where

$S_{(1)(3)}$  = correlation coefficient for part 1 and part 3 = 0.75 (from table 3),

$S_{(1)(4)}$  = correlation coefficient for part 1 and part 4 = 0.75 (from table 3), and

$\theta = 0.1$

Hence we have  $MCI_{P1} \text{ with PF1} = \{(0.75 - 0.1) + 0.75 - 0.1\}/2 = 0.65$

Similarly, MCI of P1, if it is to be included with PF2 is given by

$$MCI_{P1} \text{ with PF2} = \{(S_{(1)(11)} - \theta)\}/1; \text{ i.e.,}$$

$S_{(1)(11)}$  = correlation coefficient for part 1 and part 11 =  $-0.45$  (from table 3),

$\theta = 0.1$ .

$$MCI_{P1} \text{ with PF2} = \{(-0.45 - 0.1)\}/1 = -0.55.$$

From the MCI values, it is evident that P1 has a higher correlation with PF1 compared to PF2. Hence, P1 is assigned to PF1. After including P1 into the PF1, the updated part families and DE are shown as below:

$$PF1 \rightarrow \{P1, P3, P4\}$$

$$PF2 \rightarrow \{P11\}$$

$$DE \rightarrow \{P2, P5, P6, P7, P8, P9, P10, P12\}.$$

Similarly, for each part in DE, the appropriate PF is identified as follows:

$$\begin{aligned} \text{PF1} &\rightarrow \{\text{P1, P2, P3, P4, P5, P6}\} \\ \text{PF2} &\rightarrow \{\text{P7, P8, P9, P10}\} \\ \text{PF3} &\rightarrow \{\text{P11, P12}\}. \end{aligned}$$

### 3.3 Machine cell formation

The next task in MPCF after identifying the PF is to find the most appropriate machine cell for each PF. To simplify this task, first, the exclusive machines that are required by only one of the identified PF are singled out. After identifying the exclusive machines for each of the PF, the remaining machines that are required by more than one PF are treated with the “*relevance index-modified*” (RIMO). RIMO is useful for finding the placement for a machine (required by more than one PF) in the appropriate machine cell resulting in the minimum number of exceptional elements and voids.

For the MPCF given in table 1, the identified PF are as follows:

$$\begin{aligned} \text{PF1} &\rightarrow \{\text{P1, P2, P3, P4, P5, P6}\} \\ \text{PF2} &\rightarrow \{\text{P7, P8, P9, P10}\} \\ \text{PF3} &\rightarrow \{\text{P11, P12}\} \end{aligned}$$

Among the eight machines available, M1 is required only for PF1; M5 is required only for PF2; M7 and M8 are required only for PF3. The remaining machines M2, M3, M4, and M6, are required by more than one PF.

Thus, the initial machine cells formed are as follows:

Machine cell (MC1)  $\rightarrow$  {M1}  
Machine cell (MC2)  $\rightarrow$  {M5}  
Machine cell (MC3)  $\rightarrow$  {M7, M8}

We have machines required for more than one part family given by  $\{M2, M3, M4, M6\}$ .

**3.3a Relevance index-modified (RIMO):** The RIMO is useful for finding the placement for a machine (required by more than one PF) in the appropriate machine cell resulting

in the minimum number of exceptional elements and voids. RIMO for each PF is calculated when a machine is required for more than one PF. The machine is placed in the machine cell corresponding to the PF in which the maximum RIMO is found. A tie in RIMO can be broken arbitrarily. Gupta *et al* [27] established the fact that the impact of an increase in one exceptional element on GE is equal to the impact of an increase in 1.32 voids.

The relevance index (RI) used in the CARI heuristic is calculated by dividing the number of machining instances ( $N_m$ ) by the sum of  $N_m$  and the equivalent voids ( $N_v$ ). the formula for calculating the RI is given in equation (5):

$$RI = \frac{N_m}{(N_m + N_v)}, \quad (5)$$

where  $N_v$  is a derived number calculated by adding the number of voids created and the equivalent voids. An equivalent void is a number obtained by multiplying the number of exceptional elements by a factor of 1.32. In effect, the number of exceptional elements is converted to represent voids, thus named as equivalent voids. The RIMO measure proposed in this paper does not use the equivalent voids.

However, the number of voids is converted into equivalent exceptional elements using the same conversion factor, i.e., one exceptional element is equal to 1.32 voids. The formula for calculating the RIMO is given in the equation (6):

$$RIMO = N_M - (n_{EE} + (n_V \times k)), \quad (6)$$

where

$N_M$  = number of actual machining instances due to the addition of a machine into the existing machine cell

 $n_{EE}$  = Number of Exceptional Elements $n_V = \text{Number of Voids}$ 

$k = A$  constant. (although  $k = 1.32$  is used in this paper, it has been found that for the values of  $k$  ranging from 1.25 to 1.32, the same GE is achieved).

**Table 4.** Final machine-part cells.[illegible]

3.3b *Machine cell identification using RIMO*: Consider M2, which is required for the parts in PF1 and PF2. If M2 is considered for the machine cell relating to PF1, the RIMO is calculated as follows:

$$\text{RIMO of M2 with PF1} = N_M - n_{EE} + (n_V \times k)$$

$$N_M \text{ (if M2 is with PF1)} = 5$$

$$n_{EE} \text{ (if M2 is with PF1)} = 2$$

$$n_V \text{ (if M2 is with PF1)} = 1,$$

$$\text{and hence we have, } 5 - (2 + (1 \times 1.32)) = 1.68.$$

Similarly, if M2 is considered for the machine cell relating to PF2, we have

$$\text{RIMO of M2 with PF2} = N_M - n_{EE} + (n_V \times k)$$

$$N_M \text{ (if M2 is with PF2)} = 2$$

$$n_{EE} \text{ (if M2 is with PF2)} = 5$$

$$n_V \text{ (if M2 is with PF2)} = 2$$

$$\text{and hence we have, } 2 - (5 + (2 \times 1.32)) = -5.64$$

Since M2 has a higher RIMO value with the machine cell corresponding to PF1, it is included in it. Similarly, RIMO values are calculated for the remaining machines that are required by more than one PF. They are given as follows:

$$\{\text{RIMO of M2 with PF1} = 1.68^*; \text{RIMO of M2 with PF2} = -5.64\}$$

$$\{\text{RIMO of M3 with PF1} = -1.96^*; \text{RIMO of M3 with PF2} = -2.32\}$$

$$\{\text{RIMO of M4 with PF1} = -4; \text{RIMO of M4 with PF2} = 3^*\}$$

**Table 5.** Comparative analysis in terms of GE achieved using RI and RIMO in combination with CCI and MCI.

Data Set	Dataset Size	GE achieved using CCI for PF creation & RI for machine cells #	GE achieved using MCI for PF creation & RI for machine cells	GE achieved using MCI for PF creation & RIMO for machine cells ##
1	5 × 7	73.68	73.68	73.68
2	5 × 7	62.5	62.5	62.5
3	5 × 18	79.59	79.59	79.59
4	6 × 8	76.92	76.92	76.92
5	7 × 11	53.13	53.13	53.13
6	7 × 11	70.37	70.37	70.37
7	8 × 12	68.3	68.3	68.3
8	8 × 20	85.25	85.25	85.25
9	8 × 20	58.72	58.72	58.72
10	10 × 10	70.59	70.59	70.59
11	10 × 15	92	92	92
12	14 × 23	69.86	69.86	69.86
13	14 × 24	69.33	69.33	69.33
14	16 × 24	51.96	51.96	51.96
15	16 × 30	67.83	67.83	67.83
16	16 × 43	54.86	54.86	54.86
17	18 × 24	54.46	54.46	54.46
18	20 × 20	41.48	42.42	42.96
19	20 × 23	49.65	49.65	49.65
20	20 × 35	76.14	76.14	76.14
21	20 × 35	56.98	58.07	58.15
22	24 × 40	100	100	100
23	24 × 40	85.11	85.11	85.11
24	24 × 40	73.51	73.51	73.51
25	24 × 40	51.9	51.6	51.97
26	24 × 40	46.34	46.5	47.06
27	24 × 40	44.1	44.58	44.87
28	27 × 27	54.27	54.27	54.27
29	28 × 46	44.35	45.23	45.39
30	30 × 41	58.11	55.17	58.75
31	30 × 50	58.47	58.7	59.66
32	30 × 50	49.22	50.25	50.51
33	30 × 90	43.11	43.11	43.65
34	37 × 53	56.42	56.42	56.59
35	40 × 100	84.03	84.03	84.03

# CCI and RI refer to Cumulative Correlation Index and Relevance Index respectively, as proposed in Gupta *et al* [27].

##MCI and RIMO refer to Mean Correlation Index and Relevance Index-Modified respectively as proposed in this paper.



**Table 6.** Comparative analysis of GE of the CARIMO with existing approaches.

Data Set	Size	ZODIAC	GRAFICS	MST	GA - TSP	GA1	GA2	CARI	Best efficacy reported in the literature	CARIMO
1	5 × 7	73.68	73.68	NA	NA	NA	73.68	73.68	73.68	73.68
2	5 × 7	56.52	60.87	NA	NA	62.5	62.5	62.5	62.5	62.5
3	5 × 18	77.36	NA	NA	77.36	77.36	79.59	79.59	79.59	79.59
4	6 × 8	76.92	NA	NA	76.92	76.92	76.92	76.92	76.92	76.92
5	7 × 11	39.13	53.12	NA	46.88	50	53.13	53.13	53.13	53.13
6	7 × 11	70.37	NA	NA	70.37	70.37	70.37	70.37	70.37	70.37
7	8 × 12	68.3	68.3	NA	NA	NA	68.3	68.3	68.3	68.3
8	8 × 20	85.24	85.24	85.24	85.24	85.25	85.25	85.25	85.25	85.25
9	8 × 20	58.33	58.13	58.72	58.33	55.91	58.72	58.72	58.72	58.72
10	10 × 10	70.59	70.59	70.59	70.59	NA	70.59	70.59	70.59	70.59
11	10 × 15	92	92	92	92	NA	92	92	92	92
12	14 × 23	64.36	64.36	64.36	NA	NA	69.86	69.86	69.86	69.86
13	14 × 24	65.55	65.55	NA	67.44	63.48	69.33	69.33	69.33	69.33
14	16 × 24	32.09	45.52	48.7	NA	NA	52.5	50.98	52.5	51.96
15	16 × 30	67.83	67.83	67.83	NA	NA	67.83	67.83	67.83	67.83
16	16 × 43	53.76	54.39	54.44	53.89	NA	54.86	54.86	54.86	54.86
17	18 × 24	41.84	48.91	44.2	NA	NA	54.46	54.46	54.46	54.46
18	20 × 20	21.63	38.26	NA	37.12	34.16	42.96	41.48	42.96	42.96
19	20 × 23	38.66	49.36	43.01	46.62	39.02	49.65	49.65	49.65	49.65
20	20 × 35	75.14	75.14	75.14	75.28	66.3	76.22	76.14	76.22	76.14
21	20 × 35	51.13	NA	NA	55.14	44.44	58.07	56.98	58.07	58.15 <sup>#</sup>
22	24 × 40	100	100	100	100	100	100	100	100	100
23	24 × 40	85.11	85.11	85.11	85.11	NA	85.11	85.11	85.11	85.11
24	24 × 40	73.51	73.51	73.51	73.03	73.03	73.51	73.51	73.51	73.51
25	24 × 40	20.42	43.27	51.81	49.37	37.62	51.97	51.9	51.97	51.97
26	24 × 40	18.23	44.51	44.72	44.67	34.76	47.06	46.34	47.06	47.06
27	24 × 40	17.61	41.67	44.17	42.5	34.06	44.87	44.1	44.87	44.87
28	27 × 27	52.14	41.37	51	NA	NA	54.27	54.27	54.27	54.27
29	28 × 46	33.01	32.86	40	NA	NA	44.62	44.35	44.62	45.39 <sup>#</sup>
30	30 × 41	33.46	55.43	55.29	53.8	40.96	58.48	58.11	58.48	58.75 <sup>#</sup>
31	30 × 50	46.06	56.32	58.7	56.61	48.28	59.66	58.47	59.66	59.66
32	30 × 50	21.11	47.96	46.3	45.93	37.55	50.51	49.22	50.51	50.51
33	30 × 90	32.73	39.41	40.05	NA	NA	42.64	43.11	43.11	43.65 <sup>#</sup>
34	37 × 53	52.21	52.21	NA	NA	NA	56.42	56.42	56.42	56.59 <sup>#</sup>
35	40 × 100	83.66	83.92	83.92	84.03	83.9	84.03	84.03	84.03	84.03

Note: <sup>#</sup> Refers to the GE values that are higher than the maximum GE reported in the literature.

{RIMO of M6 with PF2 = 0.68\*; RIMO of M6 with PF3 = −3.32}, with the respective maximum RIMO value indicated by \*

The machine cells at this stage are obtained as follows:

MC1 → {M1, M2, M3} for PF1

MC2 → {M4, M5, M6} for PF2

MC3 → {M7, M8} for PF3.

### 3.4 Fine-tuning module

At this stage, it is necessary to check whether the part families identified using the MCI are final, or reallocation of parts are still possible. The possibility of part(s) reallocation is done by a procedure similar to the machine cell allocation for the machines required by more than one part

family, using the RIMO measure. In the fine-tuning module, first, the parts exclusive to each machine cell are identified, and they are retained there. RIMO is calculated for the parts that need to travel to more than one machine cell. From table 1, it is observed that P6 visits MC1 and MC2; P7 visits MC1 and MC2; P8 visits MC1 and MC2; P9 visits MC1 and MC2; P10 visits MC1 and MC2; P11 visits MC2 and MC3.

The RIMO for deciding on the allocation of a part requiring machining in more than one machine cell is calculated using equation (6).

The RIMO of P6 with MC1 is determined as follows:

$N_M$  (if P6 is machined in MC1) = 2

$n_{EE}$  created due to the machining of P6 in MC1 = 1

$n_V$  created due to the machining of P6 in MC1 = 1

**Table 7.** MPIM of the pump industry described in Murugan *et al* [55].

P/M	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15
M1	1	1	0	1	0	1	1	0	0	0	1	0	1	0	0
M2	0	1	0	1	1	0	0	1	1	1	0	1	0	0	0
M3	1	0	1	0	1	0	1	1	1	1	1	1	1	0	1
M4	1	0	1	0	1	1	0	1	1	0	0	1	0	0	0
M5	1	1	0	0	0	1	1	0	0	0	0	1	0	0	0
M6	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0
M7	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0
M8	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
M9	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
M10	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
M11	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0
M12	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
M13	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
M14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
M15	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
M16	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0

**Table 8.** Final machine-part cells for the pump industry problem using the DCA.

P/M	P3	P5	P8	P9	P10	P1	P11	P12	P2	P6	P7	P13	P15	P4	P14
M2	0	1	1	1	1	0	0	1	1	0	0	0	0	1	0
M3	1	1	1	1	1	1	1	1	0	0	1	1	1	0	0
M4	1	1	1	1	0	1	0	1	0	1	0	0	0	0	0
M1	0	0	0	0	0	1	1	0	1	1	1	1	0	1	0
M5	0	0	0	0	0	1	0	1	1	1	1	0	0	0	0
M6	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
M7	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0
M10	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0
M11	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
M14	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
M15	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
M16	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
M8	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
M9	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
M12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
M13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

The RIMO of P6 with MC1 =  $N_M - n_{EE} + (n_V \times k)$ , that is given by

$$2 - (1 + (1 \times 1.32)) = -0.32.$$

Similarly, RIMO of P6 with MC2 is, given by

$$N_M \text{ (if P6 is machined in MC2)} = 1$$

$$n_{EE} \text{ created due to the machining of P6 in MC2} = 2$$

$$n_V \text{ created due to the machining of P6 in MC2} = 2$$

The RIMO of P6 with MC2 =  $N_M - n_{EE} + (n_V \times k)$  is given by

$$(1 - (2 + (2 \times 1.32))) = -3.64.$$

Since P6 has a higher RIMO value with the MC1, it is retained with PF1 and machined in MC1.

The RIMO values of P6, P7, P8, P9, P10, and P11 with various machine cells are given below:

**Table 9.** Final machine-part cells for the pump industry problem using Mahalanobis distance sorting procedure.

P/M	P1	P2	P6	P7	P11	P12	P4	P13	P14	P3	P5	P8	P9	P10	P15
M1	1	1	1	1	1	0	1	1	0	0	0	0	0	0	0
M4	1	0	1	0	0	1	0	0	0	1	1	1	1	0	0
M5	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0
M7	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0
M14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
M10	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0
M6	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
M11	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
M15	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
M16	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
M8	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
M9	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
M12	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
M13	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
M2	0	1	0	0	0	1	1	0	0	0	1	1	1	1	0
M3	1	0	0	1	1	1	0	1	0	1	1	1	1	1	1

{RIMO of P6 with MC1 =  $-0.32^*$ ; RIMO of P6 with MC2 =  $-3.64$ }

{RIMO of P7 with MC1 =  $-2.32$ ; RIMO of P7 with MC2 =  $1^*$ }

{RIMO of P8 with MC1 =  $-4.64$ ; RIMO of P8 with MC2 =  $2^*$ }

{RIMO of P9 with MC1 =  $-4.64$ ; RIMO of P9 with MC2 =  $2^*$ }

{RIMO of P10 with MC1 =  $-3.64$ ; RIMO of P10 with MC2 =  $-0.32^*$ }

{RIMO of P11 with MC2 =  $-3.64$ ; RIMO of P11 with MC3 =  $1^*$ }, with the respective maximum RIMO value indicated by \*

From the RIMO values, we can understand that current allocation yields a greater RIMO for the parts that require machining in more than one machine cell. Hence, no more changes are possible. Table 4 shows the final machine-part cells. At this stage, if reallocation of parts happens, after reallocating the parts in the part family, where it has a higher RIMO, the RIMO for the machines required by more than one part family should be calculated using equation (6). This iterative procedure should continue until no change is possible in the part families and machine cells.

The RIMO proposed in this paper proves to be a superior measure compared to the RI measure found in [27]. RIMO allocates the machines required for more than one PF in the most appropriate machine cell, resulting in a higher GE of machine-part cells. The machine-part cells identified by the CARIMO heuristic for the benchmark dataset used in this

paper are provided in the “Appendix A”. Table 5 shows the comparative analysis in terms of the GE achieved with RI and RIMO in combination with CCI and MCI. From table 5, it can be observed that part family identification using MCI followed by machine cell formation using RIMO results in a higher GE of machine-part cells.

#### 4. Results and discussion

Table 6 shows the comparative analysis of GE achieved by the CARIMO with the existing approaches using 35 benchmark instances collected from the literature consisting of varying sizes of MPIM ranging from small ( $5 \times 7$ ) to large ( $40 \times 100$ ) well-structured and unstructured matrices. The CARIMO heuristic is coded in MATLAB R2016a. Experimental runs have been carried out using a personal computer with INTEL CORE i5 2.5 GHz processor. Since the CARIMO heuristic finds the non-singleton machine-part cells from the given MPIM, the approaches that consider finding out the non-singleton machine-part cells only are used for the comparative analysis. The approaches considered for the comparative analysis are: the ZODIAC algorithm proposed by Chandrasekharan and Rajagopalan [12], GRAFICS algorithm proposed by Srinivasan and Narendran [16], the Minimum Spanning Tree (MST) algorithm proposed by Srinivasan [19], GA-TSP algorithm proposed by Cheng *et al* [22], a genetic algorithm-based solution proposed by Onwubolu and Mutingi

**Table 10.** Final machine-part cells for the pump industry using the CARIMO heuristic.

P/M	P1	P3	P5	P8	P9	P10	P11	P12	P2	P6	P7	P4	P13	P14	P15
M2	0	0	1	1	1	1	0	1	1	0	0	1	0	0	0
M3	1	1	1	1	1	1	1	1	0	0	1	0	1	0	1
M4	1	1	1	1	1	0	0	1	0	1	0	0	0	0	0
M1	1	0	0	0	0	0	1	0	1	1	1	1	1	0	0
M5	1	0	0	0	0	0	0	1	1	1	1	0	0	0	0
M15	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
M16	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
M6	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
M7	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0
M8	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
M9	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
M10	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0
M11	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
M12	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
M13	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
M14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

[25] (referred to as GA1), a genetic algorithm-based solution proposed by Goncalves and Resende [26] (referred to as GA2), and the CARI algorithm proposed by Gupta *et al* [27]. From table 6, it can be observed that the proposed CARIMO heuristic has achieved better results and has set a higher benchmark GE for 5 out of 35 test instances, and it achieves equal to the best efficacy reported in the literature for 28 test instances. It should be noted that for the dataset 14 and dataset 20, the CARIMO heuristic achieves a slightly lower GE value of 51.96 and 76.14 whereas the maximum GE reported in the literature is 52.5 and 76.22, respectively.

#### 4.1 Performance evaluation for an industrial case

In order to validate the usefulness of CARIMO for solving the real-life industry problems, a case study relating to a pump manufacturing industry discussed in Murugan *et al* [55] has been used. As mentioned in that paper, the industry consisted of 16 machines and produced 15 parts as shown in table 7. The direct clustering algorithm (DCA) proposed by Murugan *et al* [55] achieved a GE of 33.64 with 16 exceptional elements and 55 voids as shown in table 8 and the Mahalanobis distance (MD) based sorting procedure proposed by Gupta *et al* [56] achieved a GE of 45.2 with 19 exceptional elements and 21 voids as shown in table 9. CARIMO heuristic achieved a GE of 55.88 with 14 exceptional elements and 16 voids as shown in table 10, an improvement of 66% and 23% with respect to DCA and MD based methods.

## 5. Conclusions

The CARIMO, a four-stage heuristic for the machine-part cell formation, has been proposed, and its performance has been compared with seven popular MPCF algorithms. GE of the machine-part cells formed by the heuristic presented in this paper is higher for 14.3% of the test instances, and equal to the best GE reported in the literature for 80% of the test instances. New benchmark GE values for 5 of the 35 test instances in the machine-part cell formation without singleton have been achieved. Enhancing the usefulness of the CARIMO heuristic to solve the generalized group technology problem and to find machine-part cells in the presence of multiple production factors are the future research scope of this work.

## Appendix A. MPCF Output by the CARIMO heuristic

M	2	4	5	6	1	3	7
M1	1	1	1	1	0	0	0
M4	1	1	0	1	0	0	0
M2	0	0	0	0	1	1	0
M3	0	0	0	1	1	1	1
M5	0	0	1	0	1	0	1

A.1 King and Nakornchai (1982) [57], (5 × 7)

P	1	2	3	4	5	6	7
M1	1	1	1	1	1	0	0
M2	0	0	1	1	1	1	0
M3	1	0	0	1	1	1	0
M4	0	0	0	0	1	1	1
M5	1	1	1	1	0	1	1

A.2 Waghodekar and Sahu (1984) [54],  $(5 \times 7)$ 

P	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
M1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
M2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

A.3 Seifoddini (1989) [58],  $(5 \times 18)$ 

P	1	4	6	2	3	5
M1	1	1	0	1	0	0
M2	1	1	1	1	0	0
M3	1	1	1	1	0	0
M4	0	0	0	0	1	1
M5	0	0	0	0	1	1
M6	0	0	0	0	1	1
M7	0	0	0	0	1	1

A.4 Kusiak and Cho (1992) [59],  $(6 \times 8)$ 

P	1	2	3	4	5	6	7	8	9
M1	1	1	1	1	1	1	1	1	1
M2	0	0	0	0	0	0	0	0	0
M3	0	0	0	0	0	0	0	0	0
M4	0	0	0	0	0	0	0	0	0
M5	0	0	0	0	0	0	0	0	0
M6	0	0	0	0	0	0	0	0	0

A.5 Kusiak and Chow (1987) [60],  $(7 \times 11)$ 

P	1	2	3	4	5	6	7	8	9	10
M1	1	1	1	1	1	1	1	1	1	1
M2	0	0	0	0	0	0	0	0	0	0
M3	0	0	0	0	0	0	0	0	0	0
M4	0	0	0	0	0	0	0	0	0	0
M5	0	0	0	0	0	0	0	0	0	0
M6	0	0	0	0	0	0	0	0	0	0
M7	0	0	0	0	0	0	0	0	0	0

A.6 Bector (1991) [17],  $(7 \times 11)$ 

P	1	2	3	4	5	6	7	8	9	10	11	12
M1	1	1	1	1	1	1	1	1	1	1	1	1
M2	0	0	0	0	0	0	0	0	0	0	0	0
M3	0	0	0	0	0	0	0	0	0	0	0	0
M4	0	0	0	0	0	0	0	0	0	0	0	0
M5	0	0	0	0	0	0	0	0	0	0	0	0
M6	0	0	0	0	0	0	0	0	0	0	0	0
M7	0	0	0	0	0	0	0	0	0	0	0	0

A.7 Seifoddini and Wolfe (1986) [61],  $(8 \times 12)$ 

P	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
M1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
M2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

## A.8 Chandrashekharan and Rajagopalan (1986) [62],

 $(8 \times 20)$ 

P	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
M1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
M2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

A.9 Chandrashekharan and Rajagopalan (1986) [62],  $(8 \times 20)$ 

P	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
M1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
M2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

A.10 Mosier and Taube (1985) [46],  $(10 \times 10)$ 

P	1	2	3	4	5	6	7	8	9	10
M1	1	1	1	1	1	1	1	1	1	1
M2	0	0	0	0	0	0	0	0	0	0
M3	0	0	0	0	0	0	0	0	0	0
M4	0	0	0	0	0	0	0	0	0	0
M5	0	0	0	0	0	0	0	0	0	0
M6	0	0	0	0	0	0	0	0	0	0
M7	0	0	0	0	0	0	0	0	0	0
M8	0	0	0	0	0	0	0	0	0	0
M9	0	0	0	0	0	0	0	0	0	0
M10	0	0	0	0	0	0	0	0	0	0

A.11 Chan and Milner (1982) [63],  $(10 \times 15)$ 

P	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
M1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
M2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

A.12 Askin and Subramanian (1987) [50],  $(14 \times 23)$



P.	6	7	8	18	3	4	21	24	2	17	19	20	23	5	9	10	11	12	14	16	22	13	15
M1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M2	1	1	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
M3	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M10	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M11	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M4	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
M5	0	0	0	0	0	0	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0
M7	0	1	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
M6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0
M8	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	1	1	1	0	1
M9	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	1
M14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1

A.13 Stanfel (1985) [64],  $(14 \times 24)$

P.	1	3	10	22	23	16	19	2	9	11	14	17	20	24	7	8	4	5	6	12	13	15	18	21
M1	1	1	1	1	1	0	1	0	0	1	0	0	0	0	1	1	1	0	1	0	0	1	1	0
M2	0	0	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
M8	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0
M3	1	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0
M4	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M7	1	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
M10	0	0	1	1	1	0	0	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0
M11	0	0	0	0	0	0	0	0	1	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0
M12	0	1	0	0	0	0	0	1	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0
M16	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
M9	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0
M13	0	0	0	0	0	0	0	1	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0
M14	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	1	0	1	1	0	0	0	0
M15	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0
M5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
M6	0	1	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	1	1	0

A.14 McCormick *et al* (1972) [5], (16 × 24)

P.	2	4	7	9	12	18	22	30	5	19	23	25	27	28	29	6	8	11	14	15	17	21	24	26	3	10	13	16	20
M1	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M4	1	1	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M7	1	1	1	1	1	1	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M8	1	1	1	1	1	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M11	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
M12	1	0	1	0	1	1	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
M3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0
M6	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
M9	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M15	0	0	0	0	0	0	1	1	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0
M5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	1	1	1	0	1	0	0	0
M10	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0
M14	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0
M16	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0
M2	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1
M13	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	1	0

A.15 Srinivasan *et al* (1990) [47],  $(16 \times 30)$

[illegible]

A.16 King (1980) [8], (16 × 43)

P	10	23	2	5	6	8	9	12	15	17	19	22	1	3	20	24	7	13	14	18	21	4	11	16
M1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
M2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M3	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
M4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
M6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
M7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M8	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

A.17 Carrie (1973) [65],  $(18 \times 24)$ 

P	5	10	11	14	4	6	7	8	9	19	3	12	13	1	15	16	17	2	18	20
M13	1	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
M15	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M19	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M6	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
M9	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M10	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M14	0	0	1	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
M2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M4	0	0	1	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0
M11	0	1	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0
M12	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
M17	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
M18	0	0	1	1	0	0	0	1	1	0	0	1	1	1	0	0	0	0	0	0
M5	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0
M16	0	0	0	0	0	0	1	0	1	0	0	1	0	0	1	1	1	0	1	0
M1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	1
M3	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	0
M7	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	1	1	1
M8	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	1	1
M20	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0

A.18 Mosier and Taube (1985) [66],  $(20 \times 20)$ 

P	3	12	16	22	1	2	4	10	11	15	20	13	18	19	21	23	6	7	8	9	17	5	14
M4	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
M8	1	1	1	1	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0
M14	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M20	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M1	1	0	0	0	1	1	0	0	1	1	1	0	0	0	0	1	1	0	0	0	0	0	0
M3	0	0	0	0	1	1	1	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0
M5	0	0	0	0	0	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
M6	0	0	0	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
M12	0	0	0	0	1	1	0	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0
M13	0	0	0	0	1	0	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
M18	1	0	0	0	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
M9	0	0	0	1	0	1	0	1	0	0	0	0	0	1	1	1	1	0	0	0	0	1	0
M15	0	1	0	1	1	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0
M17	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	0	1	1	0	0	0	0
M7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0
M10	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0
M2	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	1
M11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0
M16	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	1	1
M19	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0

A.19 Kumar *et al* (1986) [67],  $(20 \times 23)$



[illegible]A.23 Chandrasekharan and Rajagopalan (1989) [69],  $(24 \times 40)$ 

P.	1	9	16	17	33	10	13	14	22	35	36	2	10	12	15	23	24	31	34	8	19	21	28	37	38	39	4	5	6	18	26	27	30	3	25	32	7	20	29	40
M1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0
M3	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M21	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M22	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
M2	0	0	0	0	0	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M5	0	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
M11	0	0	0	0	0	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M19	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M31	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M20	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
M16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	1	0	1	1	0	1	1	1	1	0	0	0	0	0	0	0
M6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	0	0	0	0	0	0	0
M8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1	1	1	0	0	0	0	0	0	0
M12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	1	0	1	1	0	0	0	0	0	0	0
M15	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1	1	0	0	0	0	0	0	0	0
M18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	0	0	0	0	0	0	0
M7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
M14	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
M23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
M24	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0
M9	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0
M10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0
M17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0

A.24 Chandrasekharan and Rajagopalan (1989) [69], (24 × 40)

P.	9	33	2	11	12	15	23	24	31	34	26	30	38	39	6	7	20	29	40	5	18	27	1	16	17	8	19	21	28	37	10	13	14	22	35	36	3	32	25	40				
M1	1	1																																										
M2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0		
M3	0	0	1	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
M20	0	0	1	1	1	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
M6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0		
M8	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
M9	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
M10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
M11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
M12	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	
M15	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	
M18	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
M13	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	
M22	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M4	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M16	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	0	0	0	0	1	1	0	0	0	0	0	
M2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0		
M5	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0		
M11	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0		
M19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1	1	0	0	0	0		
M23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0		
M24	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0		
M7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	
M14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	

A.25 Chandrasekharan and Rajagopalan (1989) [69],  $(24 \times 40)$





[illegible]

A.29 Carrie (1973) [65], (28 × 46)

[illegible]A.30 Kumar and Vannelli (1987) [70],  $(30 \times 41)$

[illegible]

A.31 Stanfel (1985) [64],  $(30 \times 50)$

[illegible]

A.32 Stanfel (1985) [64],  $(30 \times 50)$

[illegible]A.33 King and Nakornchai (1982) [57],  $(30 \times 90)$

[illegible]

A.34 McCormick *et al* (1972) [5], (37 × 53)

A.35 Chandrasekharan and Rajagopalan (1989) [69],  
(40 × 100)

## References

- A.35 Chandrasekharan and Rajagopalan (1989) [69],  
(40 × 100)
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