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Maximizing Group Efficacy for the Generalized Cell Formation Problem Using Route Rank Index and Genetic Algorithm

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Abstract— *Cell formation plays a crucial role in the development of cellular manufacturing systems (CMS). Previous studies in this field have typically assumed that each part is associated with a single process plan. However, incorporating alternative routes offers additional flexibility in CMS design. This paper addresses the cell formation problem by considering alternative routes and presents a two-stage approach to address this problem. In the first stage, a Route Rank Index (RRI) is developed based on a correlation matrix to select the optimal alternative route for each part. Subsequently, a Genetic Algorithm (GA) is employed in the second stage to form part families and machine cells. The proposed approach's computational performance is evaluated using a set of generalized group technology datasets found in the existing literature. The results demonstrate that the proposed approach is highly effective and efficient when it comes to addressing the cell formation problem involving alternative routes. The ramifications of these findings in practice are substantial. Our suggested approach demonstrates its resilience and adaptability by achieving comparable or better grouping results across a wide variety of benchmark datasets. This shows the method can be used in a wide range of practical situations, including those involving matrices of varying sizes and shapes. The theoretical knowledge base on part-machine grouping strategies benefits from the comparison study. By comparing the results of our suggested method to those of well-known heuristics, we shed light on its benefits and drawbacks.*

Index Terms— *Route Rank Index; Alternative Routes; Cellular Manufacturing System; Cell Formation; Genetic Algorithm.*

I. INTRODUCTION

A Cellular Manufacturing System (CMS) has the ability to manufacture different types of products or components in moderate-sized batches, resulting in reduced production costs associated with inventory management and material transportation [1][2]. The primary objective in creating an effective cellular manufacturing system is to establish part families and machine cells. This process, commonly known as the Cell Formation Problem (CFP), aims to group machines together based on specific product characteristics. Several common production factors are considered during the CFP, including minimizing the movement of components within and between cells, managing changes in cell workload, and exceptional elements, minimizing the number of voids, and selecting alternative routes [3][4]. The Generalized Cell Formation (GCF) problem, introduced by Kusiak [5], refers to a specific type of cell formation problem where the parts involved possess alternative routes. Kusiak [5]proposed a p-median model as a solution for addressing the cell formation issue while also considering the selection of alternative routes.

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In order to provide a quantitative foundation for the cell formation problem with alternative routes, clustering algorithms based on the Similarity Coefficient Method (SCM) were developed. These algorithms utilize the SCM to measure the similarity between different parts or machines, allowing for the grouping of similar elements into clusters or cells. By considering alternative routes in the CFP, these algorithms offer an approach to objectively analyze and organize the manufacturing system based on the quantitative similarities among components [6][7].

On other hand, evolutionary algorithms have been utilized by researchers to address GCF problems. Wu, Chung, and Chang [8] introduced a hybrid simulated annealing algorithm with a mutation operator. Their approach aims to solve the GCF with the objective of reducing intercellular movements or maximizing grouping efficacy. Kao and Lin [9] proposed a two stage approach based on Particle Swarm Optimization (PSO). A discrete PSO algorithm is used in the first stage to divide machines into different cells, and part routing is assigned to each machine cell in the second stage with the goal of reducing the incidence of exceptional elements. Hashemi et al. [10] also used an innovative approach based on particle swarm optimization for cell formation problems with multiple routes. The goal was to minimize the number of moves between cells. A case study with 30 parts, 17 machines, and 62 different routings was used to evaluate if the PSO-based approach could get the near-optimal solution. For sequential machine CFP, Hazarika [11]suggested hybrid particle swarm optimization (HPSO) to reduce the intercellular movements of parts.Seven famous issues from the literature were computationally evaluated. Computational results show that the suggested approach provides solutions in representations of intercellular movement of parts that are either superior to or more aggressive than those obtained using alternative approaches.

Shiyas and Pillai [12] addressed the GCF problem using a Genetic Algorithm (GA) based on grouping efficacy. They aimed to find an optimal solution for the GGT problem by considering the effectiveness of the grouping. while Kao and Chen [13] developed an automatic clustering method. Their method focuses on automatically grouping machines and parts based on predefined criteria. Hazarika & Laha [14] developed a GA meta-heuristic to solve cell formation problems with multiple alternative processing routes, sequences of processes, and part volumes. Their objective was to minimize the total intercellular movements of parts based on the optimal alternative processing route. The study was conducted on five benchmark issues, and the outcomes demonstrated that the performance of the suggested approach was either competitive or superior to the existing methods in terms of optimal route selection and total intercellular movements of parts.

Sowmiya et al. [15] suggested a three-stage heuristic. In the first stage, utilizing the suggested Route Rank Index (RRI), which is a ranking metric that is obtained from the correlation among the alternative routes (CoRa—Correlation-based ranking), the optimal alternative route is chosen for each component. The second step involves locating machine-part cells to optimize the efficiency of the grouping process. In the final phase, a tuning module verifies the completeness of the covering set. For 25% of the test instances, the alternative routes suggested by CORA resulted in greater grouping efficacy, and for the remaining 75% of test instances, the grouping efficacy attained was as excellent as the best findings reported in the literature.

It is clear that most of the previous and current approaches to cell formation have a number of drawbacks, such as difficulties in acquiring acceptable solutions for large issues, significant processing time, and trouble in getting excellent solutions for ill-structured matrices. Another issue is that the solution is usually of low quality. While some of these techniques do well when dealing with data that can be easily categorized, others struggle when dealing with ill-structured data. On the other hand, the majority of solutions to the generalized cell formation issue remain constant for the entirety of the planning horizon. When there is a need to process a new part, the demand for additional equipment emerges in order to meet the capacity requirements.

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This paper contributes to the existing literature on GCF problems in the following way: developing a two-stage approach to identify the optimum part-machine GCF by maximizing group efficacy, where utilizing the route rank index based on a correlation matrix for selecting the best alternative route for each part in the first stage. In the second stage, a genetic algorithm was developed to form part families and machine cells.

The rest of this paper is structured in the following manner: Section II outlines the definition of the problem and performance measure. The proposed approach steps Section III. A numerical example is presented in Section IV to illustrate the proposed approach. The results are analyzed in Section V. Lastly, Section VI provides potential avenues for future research and offers conclusions.

II. PROBLEM FORMULATION

In the context of a given 0-1 part-machine incidence matrix, cell formation involves reordering its rows and columns to establish part families and machine cells. Researchers typically aim to find an arrangement that minimizes intercellular movement while maximizing machine utilization within each cell. Many existing cell formation methods assume that each part has only one alternative route, which is not realistic in manufacturing systems. Cases where each part may have alternative routes, as illustrated in *Fig. 1,* further complicate the cell formation problem. Consequently, the problem requires addressing the selection of the best alternative route, formation of part families, and creation of machine cells simultaneously. Kumar and Chandrasekaran [16] proposed the use of Grouping Efficacy (GE) as a metric to evaluate the quality of part-machine grouping as follow:

$$E = \frac{e - e_o}{e - e_v} \qquad (1)$$

Where e refers to the total number of ones in the part-machine matrix. The number of exceptions is given by e_o, and the number of voids is given by e_v.

P	R	M1	M2	M3	M4	M5	M6	M7	M8	M9
P1	R_1	1	0	0	1	1	0	0	0	1
	R2	0	1	0	0	0	1	0	1	0
	R3	0	1	0	0	1	0	0	0	1
P2	R_1	1	0	0	1	1	0	0	1	0
	R2	0	1	0	0	1	0	0	0	1
	R3	0	1	0	0	1	0	0	1	0
P3	R_1	1	0	1	0	1	0	0	1	0
	R2	1	0	1	1	0	0	0	1	0
P4	R_1	1	0	1	1	0	0	0	1	0
	R2	1	0	1	1	1	0	0	1	0
P5	R_1	0	1	0	0	0	0	1	0	1
	R2	1	0	0	1	0	0	1	0	1
P6	R_1	0	1	0	0	0	0	1	1	0
	R2	1	0	0	0	0	0	1	1	0
P7	R_1	1	0	0	1	1	0	0	0	1
	R2	0	1	0	0	0	1	0	0	1
	R3	0	1	0	1	1	0	0	1	0
	R4	1	1	0	0	0	1	0	0	1
P8	R_1	1	0	0	0	0	1	0	0	0
	R2	0	1	0	0	0	1	0	0	0
P: Part number; M: Machine number; R: Route number for each part										

FIG.1. PART-MACHINE INCIDENCE MATRIX WITH ALTERNATIVE ROUTES.

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III. PROPOSED APPROACH

A proposed approach is developed to solve the cell formation problem in CMS with the presence of alternative routes. The developed approach involves two stages: in the first stage, a route rank index based on a correlation matrix for selecting the best alternative route for each part and a genetic algorithm developed to form part families and machine cells in the second stage. *Fig. 2* depicts the sequential steps of the proposed approach in the form of a flow chart.

A. Rank Route Index

A measure for ranking is computed using the correlation between different alternative routes. This ranking measure is used to select the most suitable alternative route for each part. The correlation between two route for any part, *R1*, and *R2*, is determined by calculating the ratio of the covariance of R1 and R2 to the product of their standard deviations and is denoted as Corr (R1, R2) [17]:

$$Corr(R_1, R_2) = \frac{Cov(R_1, R_2)}{\sqrt{Var(\mathrm{R}_1) \times Var(\,R_2)}} \qquad (2)$$

Where Cov (R_1, R_2) = Covariance of the vectors *R1* and *R2*. *Var*(*R1*) = Variance of the vector *R1*. *Var*(*R2*) = Variance of the vector *R2*. The covariance of the routes *R1* and *R2* is defined as:

$$\mathrm{Cov}\,(R_1, R_2) = \mathrm{E}(R_1\,R_2) - \big(\mathrm{E}(R_1) \times \mathrm{E}(R_2)\big) \qquad (3)$$

Where E $(R_1\,R_2)$ = Expected value of *R1* and *R2*. *E*(*R1*) = Expected value of *R1*. *E*(*R2*) = Expected value of *R2*.

The MATLAB software provides a convenient "corrcoef" function that enables the calculation of the correlation matrix for alternative route options. To identify a compatible set for each alternative route of a part, the set of alternative routes from other parts that are positively correlated with it is determined. If an alternative route lacks any positive correlation with other routes, it is not assigned a compatible set. The route rank index is utilized to determine the best set of compatible alternative routes. The calculation of RRI involves adding up the correlation values of all potential pairs within each compatible set. The RRI of a compatible set comprising "R" alternative routes is calculated as shown below [15]:

$$RRI\ = \sum \mathrm{C} + (2C - 1) \qquad (4)$$

$$\forall\ pairs\ of\ alternative\ routes\ of\ the\ compatible\ set$$

Here, C represents the correlation value associated with every pair of alternative routes.

The compatible set that has the highest RRI is selected as the best compatible set. If there are multiple compatible sets with the same maximum RRI value, all of those compatible sets are taken into consideration. If the first compatible set is selected, it must be removed from the part machine incidence matrix. The procedure described above will be applied iteratively to the reduced part machine incidence matrix in order to determine the best alternative route for each part.

B. Genetic Algorithm

In the context of cell formation, GA can be applied by following a series of steps [18][19]:

Step 1: Set GA parameters:

Number of parts (*P*), number of machines (*M*), part-machine incidence matrix [x_{ij}], the population size of machine chromosome and the population size of part chromosome (*Npop*), maximum number of generations (*Gmax*), generation count (*GC*), machine cell (*MC*), and part family (*PF*), weighting factor ($0 \leq q \leq 1$), probability of crossover (*Pc*), and probability of mutation (*Pm*).

Step 2: Determine the integer values of *M/2* and *P/2*, rounding them up to the nearest integer. Then, calculate the minimum value between the two and consider it as the maximum number of cells (*MC*).

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Step 3: Create an initial population for the machine chromosome by randomly allocating machines to distinct cells within the range of 1 to *MC*.
Step 4: For each machine chromosome and part chromosome, determine the part and machine that have the maximum number of operations by following these steps:
Step 4.1: Create machine cells based on the genes present in the machine chromosome.
Step 4.2: Create part families based on the machine cells by following the provided guidelines:

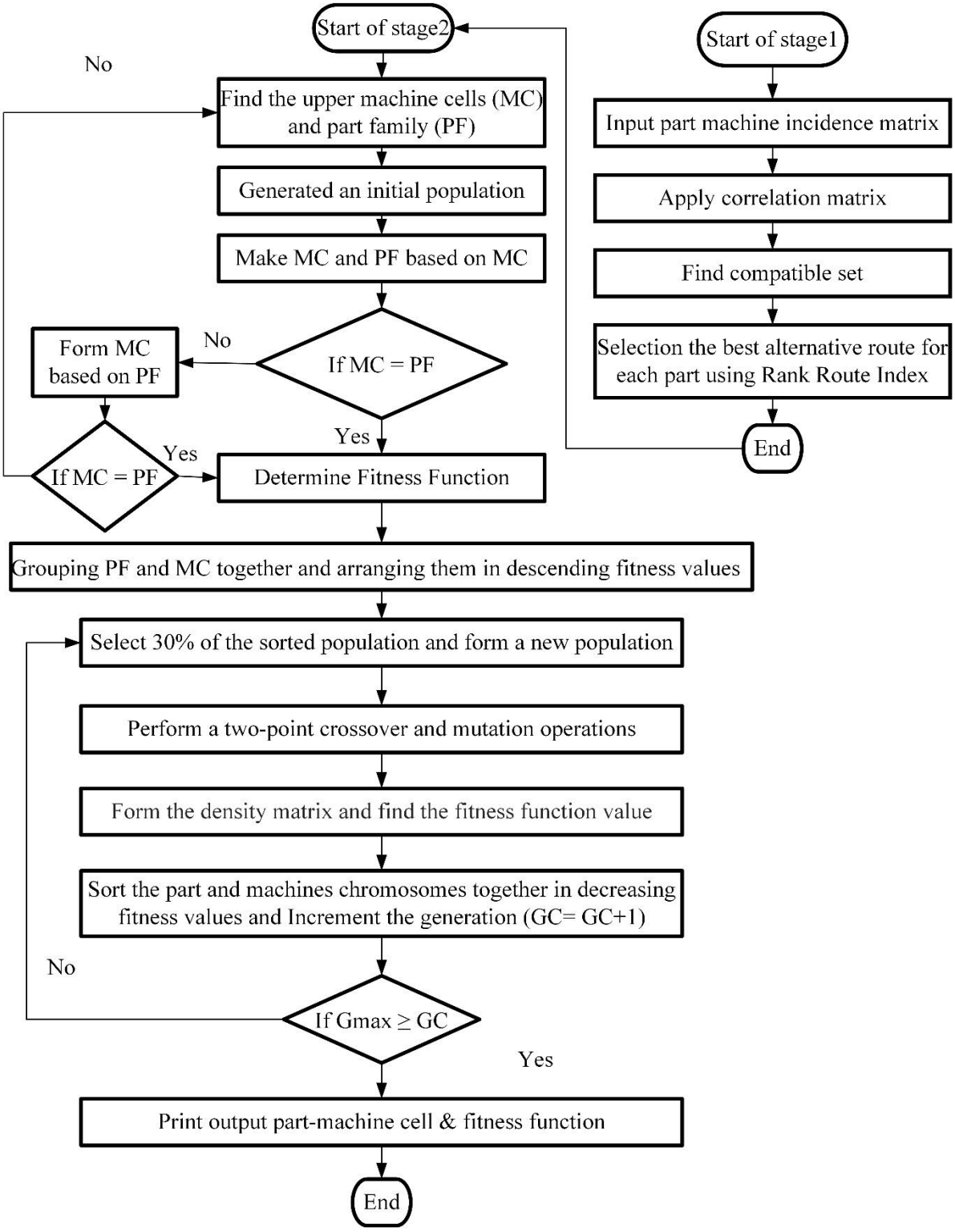

FIG. 2. FLOWCHART FOR THE PROPOSED APPROACH.

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1- Allocate the part to a machine cell where it can undergo the highest number of operations.
2- In the event of a tie for the utmost number of parts the machine can process, break the tie at random.

Step 4.3: If the number of machine cells (*MC*) is equal to the number of part families (*PF*), calculate the fitness function (*GE*), and proceed to Step 4.5. However, if the number of machine cells is not equal to the number of part families, move to Step 4.4.

Step 4.4: Create machine cells using the part families obtained in Step 2, following the provided guidelines:

1- Allocate a machine to the part family in which it can process the greatest quantity of parts.
2- In the event of a tie for the utmost number of parts the machine can process, break the tie at random.

Step 4.5: If the number of machine cells is equal to the number of part families, calculate the fitness function (*GE*) and proceed to Step 5. However, if the number of machine cells is not equal to the number of part families, move to Step 4.2.

Step 5: Arrange the part families machine cells together in descending order based on their fitness function values (*GE*).

Step 6: Select the top 30% of the sorted population, rounding the number to the nearest even value, and assign this subpopulation the size of *Npop2*.

Step 7: For each pair of consecutive part chromosomes and machine chromosomes, carry out the following steps:

1- To generate two offspring, perform a two-point crossover operation on the given individuals.
2- Mutate each of the machines and parts offspring with a mutation probability of 0.30.
3- In the case where a machine offspring has missing machine cell numbers, it should be fixed accordingly. This process involves modifying the machine offspring to ensure that the machine cell numbers are consecutive and start from the number 1 onwards.
4- If a part offspring contains missing part family numbers, repair the specific part offspring by adjusting the part family numbers. This repair process ensures that the part family numbers are consecutive and start from the first family onwards.
5- To ensure an equal number of part families and machine cells, apply additional repairs to either the part offspring or the machine offspring.
6- Calculate the density index [D_{ij}] or all machine and part offspring using the following equation [20]:

$$D_{ij} = \frac{Number\ of\ 1s\ in\ the\ part\ -\ machine\ cell}{Size\ of the\ part\ -machinecell} \qquad (5)$$

Step 8: $GC = GC + 1$.

Step 9: If $GC \leq Gmax$, proceed to Step 5.

Step 10: Present the results obtained from the topmost machine chromosome and part chromosome after implementing step 7.6. Show the corresponding part and machine chromosome, along with the grouping efficacy.

IV. NUMERICAL EXAMPLE

The numerical example is taken from Bhide et al.[21] containing 8 parts, 20 alternative routes, and 9 machine types. *Fig. 1* shows the part-machine incidence matrix. The first step in selecting the best alternative route begins by calculating the correlation matrix using Eqs. (2 & 3). The correlation matrix of the alternative routes, computed using the 'corrcoef' function provided in the MATLAB software, is presented in Table I. From Table I, a compatible set is determined for each alternative route of a part through the identification of alternative routes other of parts that exhibit a positive

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correlation with it. This compatible set is described by the color blue in Table I. Table II provides a comprehensive overview of the details pertaining to the list of compatible sets. After compatible sets are identified, The most optimal compatible set of alternative routes is determined by employing the route rank index specified in Eq. (4).For example, consider the first compatible set from Table III i.e., P11, P21, P31, P42, P52, P71, P81; the possible pairs are [{P11 P21}, {P11 P31}, {P11 P42}, {P11 P52},{P11 P71},{P11 P81},{P21 P31}, {P21 P42},{P21 P52},{P21 P71},{P21 P81},{P31 P42},{P31 P52}, {P31 P71},{P31 P81},{P42 P52},{P42 P71},{P42 P81},{P52 P71},{P52 P81},{P71 P81}]. The RRI for the first compatible set is calculated as follows:

RRI= [{$C_{P11\,P21}$+ ((2× $C_{P11\,P21}$) -1)} + {$C_{P11\,P31}$+ ((2× $C_{P11\,P31}$) -1)} + {$C_{P11\,P42}$+ ((2× $C_{P11\,P42}$) -1)} + {$C_{P11\,P52}$+ ((2× $C_{P11\,P52}$) -1)} + {$C_{P11\,P71}$+ ((2× $C_{P11\,P71}$) -1)}+ {$C_{P11\,P81}$+ ((2× $C_{P11\,P81}$) -1)}+ {$C_{P21\,P31}$+ ((2× $C_{P21\,P31}$) -1)}+ {$C_{P21\,P42}$+ ((2× $C_{P21\,P42}$) -1)}+ {$C_{P21\,P52}$+ ((2× $C_{P21\,P52}$) -1)}+ {$C_{P21\,P71}$+ ((2× $C_{P21\,P71}$) -1)}+ {$C_{P21\,P81}$+ ((2× $C_{P21\,P81}$) -1)}+ {$C_{P31\,P42}$+ ((2× $C_{P31\,P42}$) -1)}+ {$C_{P31\,P52}$+ ((2× $C_{P31\,P52}$) -1)}+ {$C_{P31\,P71}$+ ((2× $C_{P31\,P71}$) -1)}+ {$C_{P31\,P81}$+ ((2× $C_{P31\,P81}$) -1)}+ {$C_{P42\,P52}$+ ((2× $C_{P42\,P52}$) -1)}+ {$C_{P42\,P71}$+ ((2× $C_{P42\,P71}$) -1)}+ {$C_{P42\,P81}$+ ((2× $C_{P42\,P81}$) -1)}+ {$C_{P52\,P71}$+ ((2× $C_{P52\,P71}$) -1)}+ {$C_{P52\,P81}$+ ((2× $C_{P52\,P81}$) -1)}+ {$C_{P71\,P81}$+ ((2× $C_{P71\,P81}$) -1)}].

The correlation value of each pair of alternative routes is given as follows:
$C_{P11\,P21}$=0.55; $C_{P11\,P31}$=0.10; $C_{P11\,P42}$=0.35; $C_{P11\,P52}$=0.55; $C_{P11\,P71}$=1.0; $C_{P11\,P81}$=0.06; $C_{P21\,P31}$=0.55; $C_{P21\,P42}$=0.8; $C_{P21\,P52}$=0.1; $C_{P21\,P71}$=0.55; $C_{P21\,P81}$=0.06; $C_{P31\,P42}$=0.8; $C_{P31\,P52}$=-0.35; $C_{P31\,P71}$=0.10; $C_{P31\,P81}$=0.06; $C_{P42\,P52}$=-0.10; $C_{P42\,P71}$=0.35; $C_{P42\,P81}$=-0.06; $C_{P52\,P71}$=0.55; $C_{P52\,P81}$=0.06; $C_{P71\,P81}$=0.06.

RRI= [{0.55+ ((2× 0.55) -1)} + {0.10+ ((2× 0.10) -1)} + {0.35+ ((2× 0.35) -1)} + {0.55+ ((2× 0.55) -1)} + {1.0+ ((2× 1.0) -1)} + {0.06+ ((0.06) -1)} +… …+ {0.55+ ((2× 0.55) -1)} + {0.06+ ((2× 0.06) -1)} + {0.06+ ((2× 0.06) -1)}] = -2.58

Fig. 3 provides a comprehensive explanation of the procedure used to determine the RRI value for the first compatible set. Similarly, the RRI value was computed for all compatible sets, and the results are presented in Table III. Based on the data in Table III, the third set stands out as the best compatible set, possessing the highest RRI value. Consequently, it serves as the best alternative route for parts P1, P2, P5, P7, and P8. Following that, the initial part machine incidence matrix displayed in *Fig. 1* underwent a removal of the best alternative route. The resulting part machine incidence matrix is presented in Table IV. This new part machine incidence matrix will then go through the aforementioned procedure repeatedly until the optimal alternative route for each remaining part is determined. Table V exhibits the correlation matrix for the updated part machine incidence matrix, while Table VI displays the identified compatible sets along with the corresponding RRI value. From Table VI, the best compatible set with the maximum RRI value is the third set, which serves as the best alternative route for parts P3, P4, and P6. The covering set for the initial part machine matrix is given below:

Covering set = {P13, P22, P32, P41, P51, P62, P72, P82}

The binary matrix with one alternative route for each part is shown in Table VII. After obtaining the binary part machine incidence matrix, the GA basic parameters employed for solving the CMS design problem consist of a crossover probability of 0.5, a mutation probability of 0.2, a population size of 50, and a maximum number of generations set to 500[19]. The genetic algorithm was created using the MATLAB R2017b software on a personal computer equipped with an Intel Core i5 CPU with a speed of 2.4 GHz and 8 GB of RAM. Table VIII presents the part-machine incidence matrix obtained by using GA.

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V. RESULTS AND DISCUSSION

Table IX presents the details of the comparative analysis between the proposed approach and other existing approaches to verify the quality of the solutions generated by the proposed approach. This analysis utilizes 14 benchmark datasets obtained from various sources in the literature. The benchmark datasets used cover a wide range of sizes, from small matrices measuring 4 × 8 × 4 to large matrices measuring 20 × 51 × 20. Furthermore, these datasets contain both well-structured and unstructured matrices, allowing for a thorough assessment of the performance of the proposed approach. In order to gauge how well the suggested approach performs, it has been put up against two popular heuristics, HSAM2 [8] and CORA [15]. The results show that our suggested approach outperformed the CORA heuristic for grouping in two datasets (14%), and performed similarly in the remaining twelve datasets (86%). However, when compared to the HSAM2 heuristic, our suggested approach produced a higher grouping efficacy value for 3 datasets (21.5%) and a similar value for the remaining 11 datasets (79.5%). These results have significant real-world implications. Our suggested approach demonstrates its resilience and adaptability by achieving comparable or better grouping results across a wide variety of benchmark datasets. This shows the method can be used in a wide range of practical situations, including those involving matrices of varying sizes and shapes. The theoretical knowledge base on part-machine grouping strategies benefits from the comparison study. By comparing the results of our suggested method to those of well-known heuristics, we shed light on its benefits and drawbacks. The findings provide support to the theoretical basis of our approach and demonstrate its promise as an applicable approach for classifying machine parts grouping.

VI. CONCLUSIONS

This paper introduces a two-stage approach for addressing the cell formation problem with alternative routes. A route rank index is used in the first stage to find the best alternative route, and a genetic algorithm is employed in the second stage to create part families and machine cells. In order to assess the efficacy of the proposed approach, a comparative analysis was conducted to evaluate its performance relative to the HSAM2 and CORA heuristics. The experimental analysis involves testing the proposed approach on matrices of various sizes, ranging from small (4 × 8 × 4) to large (20 × 51 × 20). The matrices covered well-structured and unstructured formats, giving a thorough evaluation of the approach's potential. The comparison results show that, in terms of grouping efficacy, the proposed approach either matches or beats the HSAM2 and CORA heuristics. This shows how well the proposed approach has worked to address the generalized cell formation problem. The evaluation of the approach focused primarily on grouping efficacy and may not capture all aspects of efficiency and productivity within a manufacturing system. Other performance metrics, such as machine utilization and machine flexibility, were not considered in this study. Therefore, the overall impact of the proposed approach on manufacturing systems may require further investigation using a broader set of performance measures. Additionally, the experimental analysis only included matrices of sizes ranging from small to large, and their performance on extremely large matrices remains unexplored. Future studies should consider assessing the scalability and applicability of the approach to even larger and more complex problem instances. Overall, future research should aim to expand upon the current study by exploring various performance metrics and conducting experiments on larger problem instances to further validate and enhance the proposed approach's applicability and effectiveness in solving the cell formation problem with alternative routes.

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TABLE I. CORRELATION MATRIX OF THE ALTERNATIVE ROUTE

P	P11	P12	P13	P21	P22	P23	P31	P32	P41	P42	P51	P52	P61	P62	P71	P72	P73	P74	P81	P82
P11	1.00	-0.63	0.32	0.55	0.32	-0.16	0.10	0.10	0.10	0.35	-0.16	0.55	-0.63	-0.16	1.00	-0.16	0.10	0.10	0.06	-0.48
P12	-0.63	1.00	0.00	-0.16	0.00	0.50	-0.16	-0.16	-0.16	-0.32	0.00	-0.63	0.50	0.00	-0.63	0.50	0.32	0.32	0.19	0.76
P13	0.32	0.00	1.00	-0.16	1.00	0.50	-0.16	-0.63	-0.63	-0.32	0.50	-0.16	0.00	-0.50	0.32	0.50	0.32	0.32	-0.38	0.19
P21	0.55	-0.16	-0.16	1.00	-0.16	0.32	0.55	0.55	0.55	0.80	-0.63	0.10	-0.16	0.32	0.55	-0.63	0.55	-0.35	0.06	-0.48
P22	0.32	0.00	1.00	-0.16	1.00	0.50	-0.16	-0.63	-0.63	-0.32	0.50	-0.16	0.00	-0.50	0.32	0.50	0.32	0.32	-0.38	0.19
P23	-0.16	0.50	0.50	0.32	0.50	1.00	0.32	-0.16	-0.16	0.16	0.00	-0.63	0.50	0.00	-0.16	0.00	0.79	-0.16	-0.38	0.19
P31	0.10	-0.16	-0.16	0.55	-0.16	0.32	1.00	0.55	0.55	0.80	-0.63	-0.35	-0.16	0.32	0.10	-0.63	0.10	-0.35	0.06	-0.48
P32	0.10	-0.16	-0.63	0.55	-0.63	-0.16	0.55	1.00	1.00	0.80	-0.63	0.10	-0.16	0.32	0.10	-0.63	0.10	-0.35	0.06	-0.48
P41	0.10	-0.16	-0.63	0.55	-0.63	-0.16	0.55	1.00	1.00	0.80	-0.63	0.10	-0.16	0.32	0.10	-0.63	0.10	-0.35	0.06	-0.48
P42	0.35	-0.32	-0.32	0.80	-0.32	0.16	0.80	0.80	0.80	1.00	-0.79	-0.10	-0.32	0.16	0.35	-0.79	0.35	-0.55	-0.06	-0.60
P51	-0.16	0.00	0.50	-0.63	0.50	0.00	-0.63	-0.63	-0.63	-0.79	1.00	0.32	0.50	0.00	-0.16	0.50	-0.16	0.32	-0.38	0.19
P52	0.55	-0.63	-0.16	0.10	-0.16	-0.63	-0.35	0.10	0.10	-0.10	0.32	1.00	-0.16	0.32	0.55	-0.16	-0.35	0.10	0.06	-0.48
P61	-0.63	0.50	0.00	-0.16	0.00	0.50	-0.16	-0.16	-0.16	-0.32	0.50	-0.16	1.00	0.50	-0.63	0.00	0.32	-0.16	-0.38	0.19
P62	-0.16	0.00	-0.50	0.32	-0.50	0.00	0.32	0.32	0.32	0.16	0.00	0.32	0.50	1.00	-0.16	-0.50	-0.16	-0.16	0.19	-0.38
P71	1.00	-0.63	0.32	0.55	0.32	-0.16	0.10	0.10	0.10	0.35	-0.16	0.55	-0.63	-0.16	1.00	-0.16	0.10	0.10	0.06	-0.48
P72	-0.16	0.50	0.50	-0.63	0.50	0.00	-0.63	-0.63	-0.63	-0.79	0.50	-0.16	0.00	-0.50	-0.16	1.00	-0.16	0.79	0.19	0.76
P73	0.10	0.32	0.32	0.55	0.32	0.79	0.10	0.10	0.10	0.35	-0.16	-0.35	0.32	-0.16	0.10	-0.16	1.00	-0.35	-0.48	0.06
P74	0.10	0.32	0.32	-0.35	0.32	-0.16	-0.35	-0.35	-0.35	-0.55	0.32	0.10	-0.16	-0.16	0.10	0.79	-0.35	1.00	0.60	0.60
P81	0.06	0.19	-0.38	0.06	-0.38	-0.38	0.06	0.06	0.06	-0.06	-0.38	0.06	-0.38	0.19	0.06	0.19	-0.48	0.60	1.00	0.36
P82	-0.48	0.76	0.19	-0.48	0.19	0.19	-0.48	-0.48	-0.48	-0.60	0.19	-0.48	0.19	-0.38	-0.48	0.76	0.06	0.60	0.36	1.00

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TABLE II. COMPATIBLE SETS

Compatible set	The compatible set Members
1.	P11, P21, P31, P42, P52, P71, P81
2.	P12, P23, P61, P72, P82
3.	P13, P22, P51, P72, P82
4.	P21, P11, P31, P42, P52, P62, P71, P81
5.	P22, P13, P51, P72, P82
6.	P23, P12, P31, P42, P61, P73, P82
7.	P31, P11, P21, P42, P62, P71, P81
8.	P32, P11, P21, P41, P52, P62, P71, P81
9.	P41, P11, P21, P32, P52, P62, P71, P81
10	P42, P11, P21, P31, P62, P71
11.	P51, P13, P22, P61, P72, P82
12.	P52, P11, P21, P32, P41, P62, P71, P81
13.	P61, P12, P23, P51, P73, P82
14.	P62, P21, P31, P41, P52, P81
15.	P71, P11, P21, P31, P42, P52, P81
16.	P72, P12, P22, P51, P82
17	P73, P12, P23, P31, P42, P61, P82
18.	P74, P12, P22, P51, P81
19.	P81, P12, P21, P31, P41, P52, P62, P74
20.	P82, P12, P22, P51, P61, P72

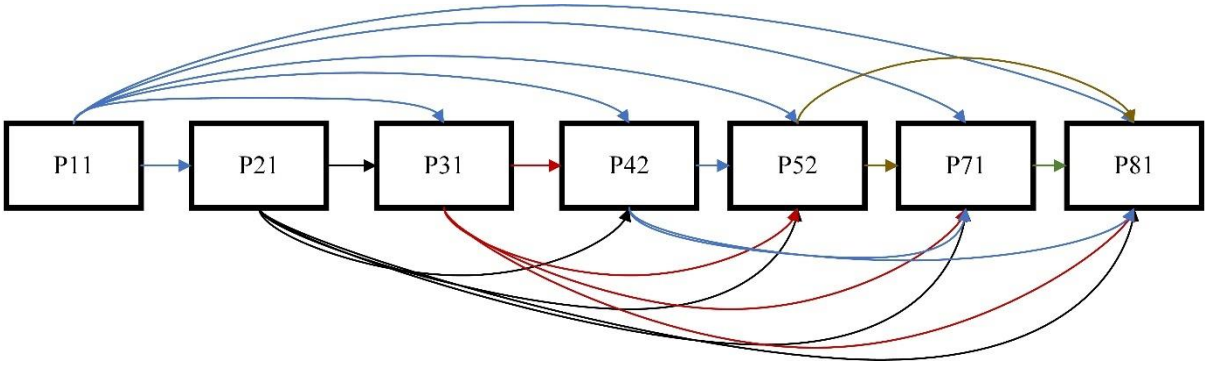

FIG. 3. PICTORIAL DESCRIPTION FOR RRI CALCULATION.

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TABLE III. RRI VALUE FOR EACH COMPATIBLE SET

Compatible set	The compatible set Members	RRI
1.	P11, P21, P31, P42, P52, P71, P81	-2.58
2.	P12, P23, P61, P72, P82	1.669
3.	P13, P22, P51, P72, P82	4.469
4.	P21, P11, P31, P42, P52, P62, P71, P81	-4.64
5.	P22, P13, P51, P72, P82	4.469
6.	P23, P12, P31, P42, P61, P73, P82	-9.55
7.	P31, P11, P21, P42, P62, P71, P81	-3.02
8.	P32, P11, P21, P41, P52, P62, P71, P81	-5.51
9.	P41, P11, P21, P32, P52, P62, P71, P81	-2.51
10	P42, P11, P21, P31, P62, P71	1.873
11.	P51, P13, P22, P61, P72, P82	1.536
12.	P52, P11, P21, P32, P41, P62, P71, P81	-5.51
13.	P61, P12, P23, P51, P73, P82	-1.06
14.	P62, P21, P31, P41, P52, P81	-5.42
15.	P71, P11, P21, P31, P42, P52, P81	-2.58
16.	P72, P12, P22, P51, P82	1.669
17	P73, P12, P23, P31, P42, P61, P82	-9.55
18.	P74, P12, P22, P51, P81	-5.56
19.	P81, P12, P21, P31, P41, P52, P62, P74	-21.8
20.	P82, P12, P22, P51, P61, P72	0.236

TABLE IV. THE REDUCED PART MACHINE INCIDENCE MATRIX

PR	M1	M2	M3	M4	M5	M6	M7	M8	M9
P31	1	0	1	0	1	0	0	1	0
P32	1	0	1	1	0	0	0	1	0
P41	1	0	1	1	0	0	0	1	0
P42	1	0	1	1	1	0	0	1	0
P61	0	1	0	0	0	0	1	1	0
P62	1	0	0	0	0	0	1	1	0

TABLE V. CORRELATION MATRIX FOR REDUCED PART MACHINE INCIDENCE MATRIX

PR	P31	P32	P41	P42	P61	P62
P31	1	0.55	0.55	0.8	-0.158	0.3162
P32	0.55	1	1	0.8	-0.158	0.3162
P41	0.55	1	1	0.8	-0.158	0.3162
P42	0.8	0.8	0.8	1	-0.316	0.1581
P61	-0.158	-0.158	-0.158	-0.316	1	0.5
P62	0.3162	0.3162	0.3162	0.1581	0.5	1

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TABLE VI. COMPATIBLE SETS AND RRI VALUE FOR REDUCED PART MACHINE INCIDENCE MATRIX

Compatible set	The compatible set Members	RRI
1.	P31, P42, P62	0.823025
2.	P32, P42, P62	1.423025
3.	P41, P32, P62	1.897367
4.	P42, P31, P62	0.823025
5.	P62, P31, P41	0.547367

TABLE VII. BINARY MATRIX OBTAINED FROM THE FIRST STAGE

P/M	M1	M2	M3	M4	M5	M6	M7	M8	M9
P1	0	1	0	0	1	0	0	0	1
P2	0	1	0	0	1	0	0	0	1
P3	1	0	1	1	0	0	0	1	0
P4	1	0	1	1	0	0	0	1	0
P5	0	1	0	0	0	0	1	0	1
P6	1	0	0	0	0	0	1	1	0
P7	0	1	0	0	0	1	0	0	1
P8	0	1	0	0	0	1	0	0	0

TABLE VIII. PART FAMILIES AND MACHINE CELLS AFTER APPLYING STAGE TWO

P/M	M1	M3	M4	M7	M8	M6	M2	M5	M9
P3	1	2	3	0	4				
P4	1	2	3	0	4				
P6	1	0	0	2	3				
P8						2	1		
P1							1	2	3
P2							1	2	3
P5				2			1	0	3
P7						2	1	0	3

TABLE IX. COMPARISON RESULTS

Reference	Size (P×R×M)	HSAM 2	CORA	Proposed Approach
Won and Kim [22]	4×8×4	100	100	100
Kusiak [23]	5×11×4	90	90	90
Moon and Chi [24]	6×13×6	83.33	83.33	83.33
Cao and Chen [13]	7×14×6	NA	95.45	95.45
Garbie et al. [25]	7×14×10	NA	66.67	66.67
Bhide et al. [21]	8×20×9	NA	69.70	70.9*
Sankaran and Kasilingam [26]	10×20×6	72.22	72.22	72.22
Won and Kim [22]	10×23×7	81.48	81.48	81.48
Adil et al. [27]	10×24×10	82.86	83.33	83.33
Won and Kim [22]	10×22×11	80.65	80.65	80.65
Shiyas and Pillai [28]	20×27×8	NA	77.78	77.78
Sofianopoulou [29]	20×26×12	49.47	50	50
Sofianopoulou [29]	20×45×14	54.29	54.64	55.77*
Nagi et al. [30]	20×51×20	79.52	79.52	79.52

NA: Not Available

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