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Cell Formation and Intra-Cell Optimal Machine Location in CMS: A Novel Genetic Algorithm (GA) Based on Machine Encoding

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Abstract: Manufacturing industries are in a constant state of competition to attract customers in a variety of methods. Group Technology (GT) is a term used in the field of manufacturing for grouping similar elements based on their similarities in production and design. Cellular manufacturing (CM) is an application of Group Technology (GT) that has gained widespread traction in Small- and Medium-Sized Enterprises (SMEs) during the recent years in order to increase the production floor's efficiency and output. A Cell Formation consists of grouping identical machinery and assigning them on similar functions. There are three main decisions involved in designing the Cellular Manufacturing System (CMS): Group Scheduling (GS), Group Layout (GL), and Cell Formation (CF). In this study, the primary challenge associated with the CMS is not only the formation of cells but also the optimal placement of machinery within each cell. This paper's objectives are therefore twofold: the formation of cells and the optimal placement of machinery within cells. For the purpose of Cell Formation and the position of machinery within the cell, a Genetic Algorithm (GA) and Encoding Scheme are employed. In this study, a Genetic Algorithm is used to classify machines and parts, while MATLAB is used for the simulation and encoding scheme. To evaluate the developed objective function and GA, a layout problem of medium size is solved. Results indicate that the proposed strategy is effective for resolving CMS issues and increasing productivity by 8.85%.

Keywords: cellular manufacturing system (CMS); cell formation (CF); optimal machine location; intracell formation; genetic algorithm (GA); encoding scheme

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1. Introduction

As a result of international competition, rising consumer expectations, and global governance policies, the global economy of the twenty-first century is dominated by the manufacturing sector. In order to increase the efficacy and output of their manufacturing systems, manufacturers are confronted with the difficulties of a short product life cycle, a lengthy time to market, and diverse consumer demands. In order to compete in the global marketplace, the world's manufacturers are presently attempting to find cost-effective, time-efficient, high-quality, and customer-satisfying production processes for their goods, which will allow them to maintain a competitive manufacturing advantage. In addition, the manufacturing systems should be able to regulate or respond rapidly to changes in product design and market demand without requiring significant investment.

To prepare for upcoming difficulties and improvements, manufacturing organizations devote a significant portion of their resources—both financial and human—to the design or redesign of their facilities. Manufacturing companies typically invest a significant sum of money in the design of new facilities or the renovation of old ones. One of the key elements that determine an industry's productivity is layout design. Industries have long employed functional layouts, but in an effort to boost production, modern layouts are gradually replacing them [1].

Manufacturers must shrink costs in order to stay alive in the present-day economy. During the last few years, many firms have begun to focus on increasing productivity with optimized utilization of human resources. Due to the optimization in labor resources, investments in equipment costs have increased. Among concerns of these strategies are momentous savings in the direct employment cost, which in effect makes material supervision cost more imperative than before. Material handling cost reductions can be obtained by designing effective layouts [2]. Effective layouts acquired by solving machine and facility layout problems successfully can keep an organization competitive in the global market.

Group Technology is applied in Cellular Manufacturing Systems (CMSs), which are used to create production system architectures. A CMS is a system that enables the processing of many parts in cells that share the same geometry, design, or method. A basic stage in Group Technology (GT) and CMS is cell creation. It benefits from both job shop and flow line production. In manufacturing systems, cells are classified as either process or product types. In process layouts, parts with different qualities but the same manufacturing method are made in the same cell, whereas in product layouts, similar products based on their shape, design, and other attributes are processed in the same cell [3] as depicted in Figure 1. The Cellular Manufacturing System is an effective use of Group Technology that can combine flow line and job shop standards, adapt to changing market demands, and overcome some of the limitations of the past. The Cellular Manufacturing System is a good example of a Group Technology application that meets contemporary needs [4]. Furthermore, because of its short life cycle, which causes variations in product mix and demand over time, it is more realistic to focus on dynamic rather than static situations in the manufacturing system. These days, dynamic CMS has drawn the attention of a majority of researchers, since it is more realistic and useful. The issues of Cellular Manufacturing Systems and dynamic environments have attracted significant attention from researchers in recent times [5]. Reduced movement of parts, throughput time, customer order response time, and work-in-process (WIP) are a few of the benefits of cellular manufacturing. All of these reductions contribute to a rise in profitability. The reduction in response time to customer orders enables businesses to respond swiftly to alterations in customer requirements and, as a result, to maintain a competitive advantage despite the rapid evolution of market demands.

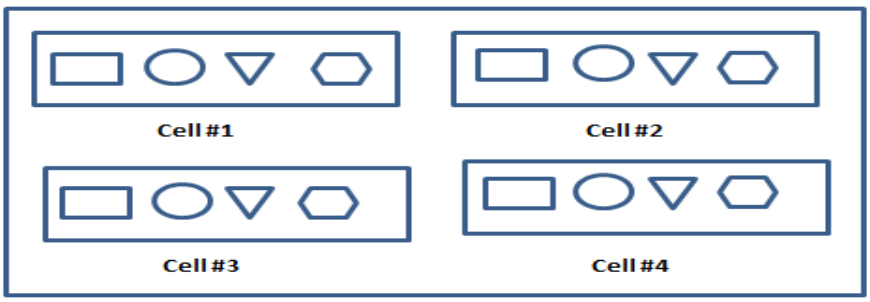

Figure 1. Cellular layout.

The parts in a Cellular Manufacturing System are grouped according to common characteristics such as shape, tolerance, and process plan. We refer to these sets of components as part families. In CMS, there are numerous machine cells, and within each machine cell are various machines devoted to producing one or more part families. By cutting down on setup, wait, and move times, the CMS installation shortens throughput times. It also

lowers material handling costs and inventory levels while speeding up market reaction times [6].

The sequencing of the machines in each cell or group and the IDs of part families are all part of the Cellular Manufacturing System (CMS) implementation process. Cell creation is the grouping of machines into cells on the shop floor [7]. Grouping machines (Cell Formation) is a crucial step in the design of a Cellular Manufacturing System [8]. Parts that share the same manufacturing needs are now organized into part families and assigned to distinct pieces of machinery for processing. In the realm of cellular manufacturing, the generation of cells or groups of machines is a thoroughly researched problem with a wealth of reviews and taxonomies available [9,10], but the layout delinquent in CMS has rarely captivated researchers' attention as much as Cell Formation (grouping of machines) [11].

The objective of facility layout is to arrange a collection of facilities so as to minimize the qualitative (information flow, noise disturbance, and work between parts) or quantitative (material handling cost, product manufacturing cost, scheduling cost, etc.) objective functions on the shop floor [12].

Material handling is considered the most time-intensive objective function in manufacturing system layout design. The objective of CMS facility layout problems is to determine the arrangement of facilities in machine cells and the shop floor layout of cells. The primary objective of this paper is to optimally position machines within the cell. Genetic Algorithms (GAs) with machine encoding schemes have been proposed for this purpose. The remainder of this paper is organized as follows. In Section 2, the literature review is presented. The Genetic Algorithm and mathematical model are, respectively, illustrated in Sections 3 and 4. The analysis of results is discussed in Section 5. Finally, the paper concludes with Section 6.

2. Literature Review

CMSs emphasize the organization of production processes into self-contained cells, each of which is capable of producing a distinct product family. In the context of Small- and Medium-Sized Enterprises (SMEs) in the Kingdom of Saudi Arabia (KSA), adoption of a content management system (CMS) has become a strategic imperative. The Kingdom of Saudi Arabia's pursuit of economic diversification and its Vision 2030 initiative highlight the importance of cultivating a competitive and adaptable manufacturing sector. CMSs have become a focal point of research and implementation efforts due to their potential to enhance operational efficiency and agility.

In this modern manufacturing research of Group Technology, the problem of Cell Formation is considered as the subject of study. This research is essential to the development of Group Technology (GT), as it involves the identification of similar parts of families and groups of machines, such that each group of machines processes the number of a part family. This Cell Formation offender is investigated using a variety of methods and techniques to address the issue. There are two broad approaches to solving Cell Formation: the design-oriented approach and the production-oriented approach [13].

2.1. The Design-Oriented Approach

In the design-oriented technique, the parts are congregated into families based on the classification and design features; after grouping, a coding technique is executed on the parts to be produced. The coding technique and overview of classification is developed by [14]. A number of researchers have considered artificial-based neural networks in order to arrange part families centered on the design structures and to develop a method of self-organizing neural networks by focusing manufacturing and design features simultaneously, recommending a technique named interactive activation and competition [15].

2.2. The Production-Oriented Approach

In order to form machine cells, production-oriented methods are established on the routing information and processing of parts. The absolute technique of production-oriented

methods is known as Production Flow Analysis (PFA), propagated by Hameri and Ari Pekka [16]. PFA's primary objective is to ensure the novelty of part families and accompanying machine assemblies for Group Layout by utilizing production route cards rather than part drawings. The work parts with identical or similar routings are classified into part families. These part families are then arranged to form machine cells in accordance with the layout of Group Technology (GT). In order to identify part families, the PFA technique utilizes manufacturing data rather than design statistics. It can obliterate two potential differences that may occur during part classification and coding:

- Parts with dissimilar geometries may entail parallel or uniform indistinguishable process routing.
- Parts with similar geometries may nonetheless require process routings that are fairly different.
- This technique consists of three continuous stages. The first stage is known as the factory flow analysis. In this stage, the statistics of part processing requests is examined to acquire an overall flow between the groups of machines. In the second stage, known as the group analysis, focus on information about the relationship between parts and machines is utilized in order to form part families. The third stage scrutinizes the arrangement of the machine's layout and operations by using the flow line concept [16].

2.3. The Hierarchical Clustering and Nonnierarchical Clustering Approaches to Solve the Cell Problem Layout

These techniques function on the input statistics labeled in relationship to the similarity or distance function by forming a hierarchy of clusters. These approaches encompass two stages. The first stage computes the similarity coefficients among each pair of parts. The second stage determines in what way the pairs with approximately correspondent similarity levels should be merged [17,18].

Nonhierarchical clustering methods generate a single data partition based on an input set of clusters to be formed using a similarity or distance function and a predetermined number of clusters. The tendency to design a varying number of clusters distinguishes the nonhierarchical clustering approach from the hierarchical approach as its primary advantage. In the initial stages of clustering, the data participants are not permanently tied to the group [19]. The primary disadvantage is that the number of clusters to be formed must be given strong priority by requiring the natural clusters to be divided or merged. The nonhierarchical clustering methods are developed by [20] taking into account the Ideal Seed Nonhierarchical (ISNC) method based on the evaluation of grouping efficiency, which measures within-cell machine utilization and intercell movement [20,21].

2.4. Mathematical Programming Techniques

The mathematical programming techniques for clustering problems are linear or nonlinear integer programming techniques. The Cell Formation problems are formulated as optimization problems, with the objective function being the maximization of the total sum of similarities between each pair of individuals (parts or machines) or the minimization of the distances between each pair. The distinctive benefit of employing these techniques is that they permit the combination of other manufacturing data, such as processing times, operation sequence, etc. These methods, however, are computationally exhaustive for large problems [22,23]. Different programming techniques, such as the branch and bound method and bond energy, are proposed to solve Cell Formation problems. In addition, goal programming techniques and evolutionary programming techniques [24,25] have been proposed.

2.5. Heuristics Approaches

- Apart from the mathematical programming approaches to resolve Cell Formation problems, most methods are founded on the heuristics which are accumulated into

array-based clustering. Other heuristics, which are the combination of multiple techniques, have also been developed by several researchers, including [26,27]. The drawbacks associated with heuristic approaches are as follows:

- Machine operations arrangements are ignored.
- Numerous visits for the product of the same machine are not considered.
- Volumes of the intercellular moves are not considered.
- Material handling cost is ignored.
- Multiple visits to the same machines are disregarded.
- Volume of production, material handling cost, and component cost are not considered.

To deal with these shortcomings, researchers developed the GA and Hybrid GA approaches to solve the CMS problems very effectively.

GA and Hybrid GA Approaches to Solve Cell Formation and Machine Layout

The cell arrangement concept was introduced by Filho and Tiberti [28] via GA and established for group encoding, as opposed to conventional machine encoding, in order to simultaneously create manufacturing cells and select CM groupings. Wu et al. designed a hierarchical GA with intrinsic features, such as a hierarchical chromosomal structure, in order to encode two crucial cell design decisions. These features include (i) a new selection scheme that dynamically takes into account two correlated fitness functions and (ii) a group mutation operator to increase the probability of a mutation occurring. The application of this method yielded results that demonstrate its effectiveness in improving solution quality and accelerating convergence. Deep and Singh [29] proposed utilizing GA to design dependable machine cells and configurations for the production of dynamic parts. The objective was to develop a production cost model that accounts for various manufacturing costs, including production volume, multiple process routes, machine capacity, material handling, and subcontracting of component operation. Rezazadah and Khiali [30] utilized a two-layer GA to find a design for dependable CMs that can assist in achieving near-perfect solutions with the lowest potential transportation costs. Using computer tests, the usefulness of the proposed algorithm was demonstrated. Tabriz, Iran's Iranian Diesel Engine Manufacturing Company presented the results of a design case study for a CM. Javadi et al. [26] developed an electromagnetism-like (EM-like) method and a Genetic Algorithm to solve the design problem of inter- and intracellular architecture in a dynamic environment. The goal was to reduce the overall cost of material handling flows during cell rearrangement and intra- and inter-cell. In order to evaluate the performance of this pairing of two algorithms, statistical tests were conducted on a number of numerical examples divided into small, medium, and large problems that were solved using the proposed method. The test results demonstrated that the proposed strategy outperformed the competing algorithms. The primary objective of Modrak et al. [31] was to discover how to solve the issues of Cell Formation and layout design. Changes to the GA parameter set resulting from research have an effect on the CMS issue. Since noise factors are represented by the size of the matrix in that study, they used the Taguchi method to determine the optimal combination of GA parameters that can increase the algorithm's efficiency and to determine whether this optimal combination is influenced by noise factors. The objectives of the proposed GA in Ponnambalam's study [32] include simultaneously designing the input and output locations for each cell's stations and figuring out the material handling systems' flow paths.

The total material handling cost for the GA that was used to optimize the solution design was the lowest. The suggested approach was put to the test on four different layouts using various sets of the original problem data. The tests' findings led to the conclusion that the suggested logarithm can provide appropriate solutions and adhere to realistic computational constraints. A hierarchical GAs technique was employed by Chandrasekar and Venkumar's research [33] to address the issues of cell generation and cell machine layout design. The input data for designing the CMS consists of a machine part incidence matrix with an operational sequence. Both grouping efficacy and grouping

efficiency were used to assess the effectiveness of the CMS. When the proposed algorithm was applied, the consistency and the outcomes revealed that it performed better than the counterpart from earlier approaches. Forghani and Mohammadi [34] developed an integrated strategy based on developing the GA to successfully resolve such complicated problems in reasonable computational time in order to simultaneously tackle the Cell Formation and layout challenges. Alternative process routings served as a representation of design inputs. The proposed approach takes into account factors such as the demand for parts, machine capacity, and multirow machine arrangements within cells, cell size, aisle distances, etc., to make it more practical. Applying the suggested GA to a number of already published instances from the literature allowed for an evaluation of its performance. According to the findings, compared with the sequential design approach, decisions about Cell Formation, inter- and intracellular layouts, and part routing result in a significant decrease in overall material handling costs. In order to reduce the overall cost of part relocations, as well as cell reconfigurations, a bi-objective optimization model is created to incorporate the Cell Formation and inter/intracell layouts in continuous space while taking fuzzy conditions into consideration [35]. In order to identify concurrent machine cells, the layout of facilities (machines, workstations, and cells), processing routes, and processing speed of operations while minimizing electric energy consumption and material handling costs, Forghani et al. [36] proposed a hybrid solution approach that combines GAs and SA (Simulated Annealing). The computational outcomes demonstrated the efficacy of the suggested strategy and its superiority to CPLEX, conventional GAs, and SA.

3. Research Design

The research flow is shown in Figure 2. The first step is to define the objectives and problems associated with cellular manufacturing design. In order to form the cells, a novel Genetic Algorithm (GA) based on an encoding scheme is carried out. The encoding scheme is deployed in machines. The encoding scheme is used as input for the Genetic Algorithm (GA). After that, the GA is deployed to the specific cellular manufacturing problem for Cell Formation. MATLAB is used for model initiation. The Cell Formation and intracell machine arrangement are designed based on MATLAB simulation results. All the grouped (formation) cells are analyzed prudently based on their performance. For validation and optimization, a small- and medium-sized problem is presented. For this purpose, a mathematical problem with objective function is designed to maximize production rate and minimize production cost. This research will end with the optimization of results. If there are any problems remaining in the optimization, then the research will be repeated to sort out the problem.
Steps involved in research methodology are described in detail below.

3.1. Research Problem

The issues related to manufacturing involve machines' locations and relocations, bottlenecking of machines and parts, inter- and intracellular material transferring, part routing, dynamics, part demands, exceptional elements, machine distances, number of voids, cell load variation, cell reconfiguring, operation, and completion times, which result in higher costs and lower production. In order to solve these issues, a Cellular Manufacturing System is designed by using a novel Genetic Algorithm (based on encoding scheme).

3.2. Genetic Algorithm Based on Encoding Scheme

The 2nd stage of this research consists of two phases. In the first stage, an encoding scheme is deployed in machines. This encoding scheme is used as input for the Genetic Algorithm (GA). In the 2nd stage, the GA is deployed to the specific cellular manufacturing problem for Cell Formation. The steps involved in GA-based encoding are described below.

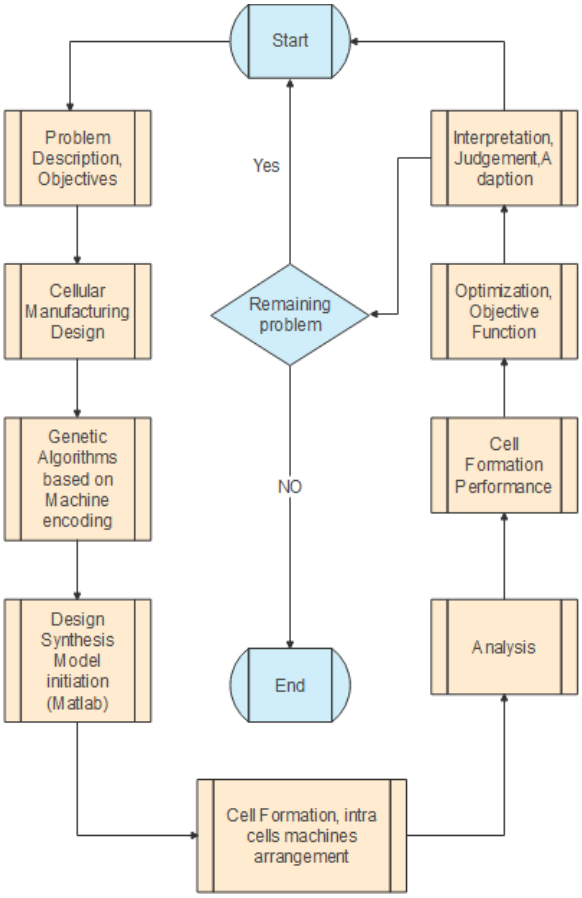

Figure 2. Research methodology flow diagram.

3.2.1. Encoding Scheme

Individuals need encoding for the representation of solutions stored in it. In the current problem, a machine location matrix is considered as a chromosome, and real number encrypting is presented. Figure 3 indicates the chromosomes, which represent a layout solution for machine arrangement. The magnitude of the chromosome is close to the number of machines assigned on behalf of the layout. The numbers shown in the chromosomes indicate the machine number, while the position of this number in the matrix indicates the location of the machine in the layout. From Figure 3, the number "5" indicates that machine 5 is located in Loc_{L25} in layout type. Similarly, from Figure 2, machine 1 is positioned at Loc_{L54}.

4				
	2			5
			3	
			1	

Figure 3. Machine location matrix and value encoding.

3.2.2. The Genetic Algorithm (GA) for Cell Formation

In the Genetic Algorithm (GA), the chromosomes are encoded with all of the required solutions. The fitness of each chromosome is then assessed, and two fit chromosomes are chosen for reproduction. The chromosomes chosen for reproduction are known as parents. The crossover of parental chromosomes results in the formation of two offspring. These offspring share characteristics with their parents. During crossover, it is possible that some genetic material from the parent chromosome will be lost. Therefore, mutation is performed. After mutation, the fitness value of the offspring is determined. Then, in accordance with the replacement scheme, these progenies are introduced into the new generation by replacing some of the older individuals. This concludes one cycle of the Genetic Algorithm. After one generational cycle, a new generation is formed. The Genetic Algorithm repeats the same procedures to produce the subsequent generations.

Initial Population

The procedure to create the initial population and the concentration of fit and weak individuals in the initial population are very important. If the initial solution consists of only fit individuals, then the GA will produce results in the short term.

Fitness Evaluation

An individual's fitness is determined by a mathematical value derived from the solution stored in a chromosome. The fitness function is a function that describes the mathematical value of individuals. The greater a person's capabilities, the closer the optimal solution will be to them. In the current problem, the fitness function is represented by the following mathematical expression:

$$f(s)_L = \max[\sum_{j=1}^{M_L} \frac{F_{ijmL}}{d_{jmL}} \times X_{ijmL} \times X_{ijlL} \times X_{imlL}] \quad \forall\, L = \{Ass, cel, machine, Pr\}0 < s < S \tag{1}$$

where

Ass stands for Assign, cel stands for cell, Pr stands for probability, and
F_{ijmL} is the quantity of the part i moved from the machine j to m in layout type L;
d_{jmL} the distance of machine j from m in layout type L;
X_{ijmL} is the binary variable equivalent to 1 if part i is moved from machine j to m in layout type L, and it is zero otherwise;
X_{ijlL} is the binary variable equivalent to 1 if machine j is on location l in layout type L, and it is zero otherwise;
X_{imlL} is the binary variable equivalent to 1 if machine m is on location l in layout type L, and it is zero otherwise.

Subject to the conditions already explained while defining the objective function, in the above-mentioned fitness function, s indicates any individual in the population, and S describes the population size. The other variables used in the fitness function equation are explained in the previous section.

The Selection

Selection is the process of selecting the two parents. The GA proceeds with this study's tournament selection. The choice of the tournament is intended to be made by the parents. Two people are chosen at random to participate in the tournament. Among these two offspring, the best individual is placed into the coupling pool, and this procedure is repeated until the pool is full. Many researchers utilize this strategy because it is effective.

The Crossover

This study uses the precedence preservative (PPX) crossover because, in comparison with other crossovers, PPX is particularly effective in creating a solution. A detailed description of the PPX crossover procedure is shown in Figure 4. The numbers 1 or 2, which are similar to the parent numbers 1 and 2, are randomly filled into the random vector with length (where length is comparable to the frequency of jobs in the permutation flow shop). The numbers 1 and 2 denote the orders that were given by parents 1 and 2, respectively. The order indicated in the random vector is permitted by the extreme left genetic elements from the parents. When a parent's gene is activated, it is squeezed into the children's chromosomes, and the same gene from another parent, chosen from left to right, is then eliminated. This process continues until all the parents' chromosomes are empty, resulting in children from all genes.

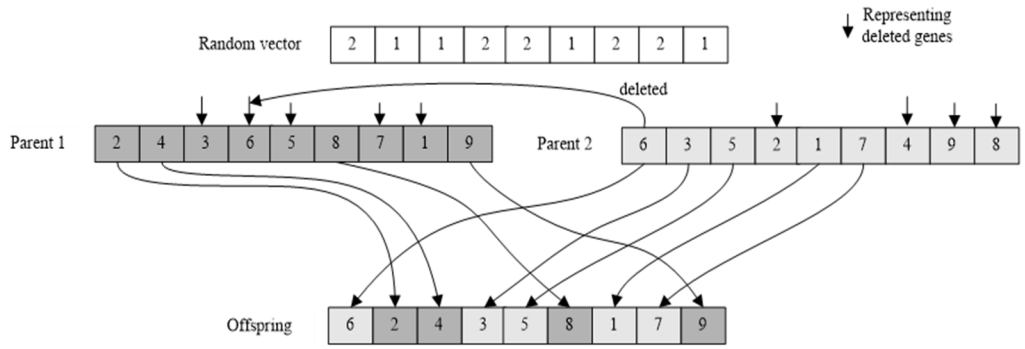

Figure 4. Precedence preservative crossovers (PPX).

The quality of the solution is substantially impacted by the crossover operator in Genetic Algorithms. The crossover operator should be able to impart positive traits from their parents to their children. The crossover operators are made in such a way that they take into account population diversity in addition to transferring desirable traits to progeny. As seen in Figure 4, a new crossover operator is introduced for the current situation in order to incorporate these features.

Mutation

After crossing, mutation is carried out to boost population variety. In Figure 5, two randomly chosen genes, 3 and 1, are switched around to create a mutant offspring. The most common type of mutation is swap mutation. The swap mutation mechanism is shown in Figure 6. Two occupied genetic components are chosen at random from an offspring's location matrix during swap mutation. As seen in the picture, both of the targeted genes have changed locations

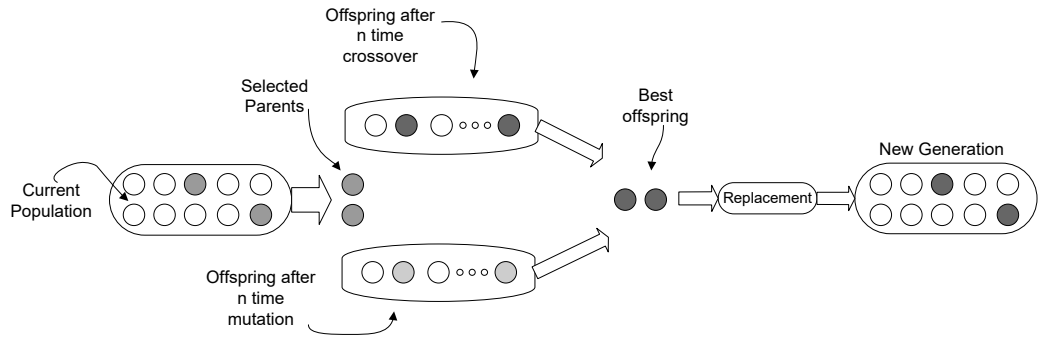

Figure 5. Mutation.

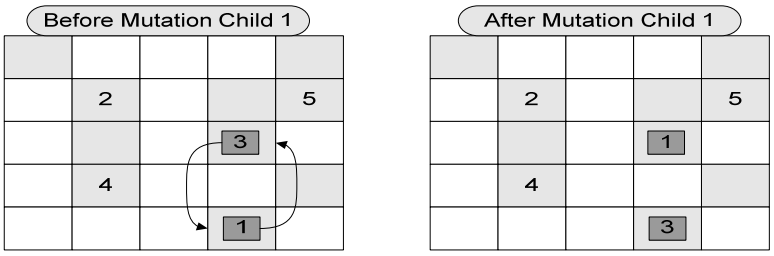

Figure 6. New generation scheme.

3.2.3. The Replacement

The final stage of the breeding cycle is the replacement (the breeding cycle involves the processes from crossover to replacement). Two chromosomes were selected for the crossover to create two offspring, but in new generations, all four of these individuals will not enter. This is to maintain the constant size of the population. So, two individuals of the population must be replaced with newly generated chromosomes. Fundamentally, two types of methods are available for sustaining the population: steady-state updates and generational updates.

3.2.4. Selection of New Generations

After replacement, a new generation is obtained which will go through all the traditional steps of GA, which are indicated in Figure 6. It is to be noted that in a traditional Genetic Algorithm, the offspring formed are recognized to enter in the next generation if they do not have the good topographies of their parents. Therefore, some good characteristics of parents may be lost during the process. In this dissertation, the new generations' scheme proposed by Q. Liu, Saif Ullah, and C.Y. Zhang [37] is used. The generation scheme presented by them permits the offspring encompassing the good features of their parents to go into the new generation. The new generations' scheme is shown in Figure 6. In this generation method, tournament selection is used to select parents. The selected and nominated parents create different children after n times crossovers and mutations. The best two offspring that comprise the worthy characteristics of their parents are nominated from all the offspring. The nominated offspring are used to switch the parents to create the new generation.

This scheme ensures that the right features of parents are conserved in new generations.

3.2.5. Termination

The termination condition in a GA indicates the condition at which the GA stops. Different termination conditions are shown in Table 1. In this research, for the best result, the maximum number of generations is accepted as the stopping criteria.

Table 1. Termination conditions for GA [37].

Maximum Generations	Algorithm Will Stop When Maximum No of Generations Is Produced
Elapsed Time	When specified time is finished. Comment: The process will stop if the maximum number of the generations has been reached before the indicated time has elapsed.
No Change in Fitness	If there is no change in the maximum fitness value for the specified number of generations.
Stall Generations	If improvements are not found in the objective function for the sequence of successive generations of the stall generations
Stall Time limits	If the improvement is not found in the objective function during an intermission of time in seconds equal to the stall time limit.

Once the number of parts processed on every machine in every cell is calculated, then machines are arranged in a layout using the proposed GA.

4. Mathematical Model

A mathematical model is presented to evaluate the performance of Cell Formation. The objective function and constraints of the mathematical models are defined below.

4.1. Objective Function

It is crucial to arrange or designate a place for each machine in each cell in order to minimize production costs and flow times. The objective function with constraints, which is important for decreasing flow time and raising production rate, is provided below. Every cell has the same set of constraints and the same goal function.

$$Objective = \max[\sum_{j=1}^{M_L} \frac{F_{ijmL}}{d_{jmL}} \times X_{ijmL} \times X_{ijlL} \times X_{imlL}] \quad (2)$$

Subject to

$$\sum_{l=1}^{Loc_L} X_{ijlL} \leq 1 \quad \forall\, j = 1, 2, \ldots, M \text{ and } L = \{Ass, Cel, \text{Pro}\} \quad (3)$$

$$\sum_{j=1}^{M_L} X_{ijlL} \leq r_{jL} \quad forall\ l = 1, 2, \ldots, Loc_L \text{ and } L = \{Ass, Cel, \text{Pro}\} \quad (4)$$

$$\sum_{j=1}^{M_L} F_{ijmL} \times X_{ijmL} \leq dem_{iL} \quad \forall\, i = 1, 2, \ldots, N \text{ and } L = \{Ass, Cel, \text{Pro}\} \quad (5)$$

where

F_{ijmL} is the quantity of the part i moved from machine j to m in layout type L,
d_{jmL} is the distance of machine j from m in layout type L,
X_{ijmL} is the binary variable equivalent to 1 if part i is moved from machine j to m in layout type L, and it is zero otherwise,
X_{ijlL} is the binary variable equivalent to 1 if machine j is on location l in layout type L, and it is zero otherwise,
X_{imlL} is the binary variable equivalent to 1 if machine m is on location l in layout type L, and it is zero otherwise.

The first constraint states that for $\forall$, $j = 1, 2, \ldots, M$, and $L = \{Ass, Cel, \text{Pro}\}$, all locations are assigned by only one location. The second constraint states that for $\forall$, $l = 1, 2, \ldots, Loc_L$, and $L = \{Ass, Cel, \text{Pro}\}$, each replicate of a machine in a particular layout type is to be assigned one location. The third constraint indicates that for $\forall\ i = 1, 2, \ldots, N$, the total quantity of the parts to be produced in $\forall\ L = \{Ass, Cel, \text{Pro}\}$ should not exceed its production demand in that layout type.

Loc_L indicates a location matrix for each type of layout. Since the number of machines in each layout type is different, the location matrix has different sizes depending on the number of machines assigned to the layout type.

4.2. Case Study of Automobile Industry (SMEs)

A CMS can be designed by small- and medium-sized machine manufacturers. When various actual manufacturing costs are considered, these types of machinery can be relocated. The SAMCO Ltd. (Jubail, Saudi Arabia) has a number of significant automotive groups in the KSA. The proposed model was applied to Cell Formation design and manufacturing data to demonstrate its applicability. The capacity of the SAMCO automobile manufacturing facility, which operates 8 h per day, 26 days per month, and 12 months per year, is 2880 h per year. Pins, pierce punches, bottom dies, guides, and pallet guide pins are manufactured using a variety of machines, such as drilling machines, CNC milling

machines, traditional milling machines, electro-erosion machines, etc., with a production horizon of two months and two production cycles. Table 2 depicts the product routing and process plan for the industrial case study, while Table 3 depicts the parts/machine incidence matrix.

Table 2. Product Information.

Part No.	Machine Sequence	Processing Time (Sec)	Demand
P1	1-2-5	90-60-45	3500
P2	13-6-7-8	120-300-360-280	1400
P3	4-11-12-15	75-60-120-240	2200
P4	3-1-6-7-9-12-14	200-80-260-340-500-90-4200	1200
P5	14-15-10	3000-340-720	1800
P6	2-6-7-10-13-14	80-290-210-640-110-3500	4200
P7	4-5-15-8-7-9	90-90-180-210-390-170	4600
P8	3-2-1-6-8-9-10-15-7	150-110-140-270-240-190-70-300	7000
P9	14-15-1-9	3500-320-110-180	3200
P10	5-7-11-13	90-240-110-140	1800

Table 3. Parts/Machine Incidence Matrix.

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

Combining four GA fundamental parameters—0.5 for crossover probability, 0.2 for mutation probability, 50 for population size, and 500 for the maximum number of generations—allows for the resolution of the CMS design problem. The GA program was created using MATLAB (R2022a) software. A discussion of the results is presented in detail in the section below.

5. Results Discussion and Analysis

The results obtained for each cell are indicated below.

5.1. Machine Encoding for Cell 1 and Formation of Cell 1 by GA

In order to avoid the complexities of the programming, the following machine numbers were programmed instead of the original numbers. Machines are encoded by using MATLAB. Table 4 shows the nomenclature of machines. Machines are encoded with specific numbers using MATLAB programming. These encoded machines are used as input for Cell 1 formation.

Table 4. Machine Encoding for formation of Cell 1.

5a	5b	5c	14a	14b	14c	9a	9b	9c	1a	1b	1c	11	7	20
b	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Figure 7 shows the formation of Cell 1. Cells are formed by using Genetic Algorithm (GA). In Cell Formation, machines with similar functions are grouped into similar group, as shown in the table below.

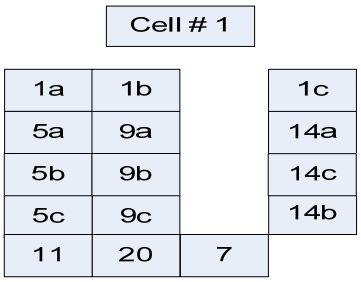

Figure 7. Formation of Cell 1.

Table 5 shows the machine chromosomes and intracell machine arrangements. Similar machines are located in a similar group based on their product and design functions.

Table 5. Machine Chromosome and arrangement of Machines in Cell 1.

Machine Chromosomes	**4 4 3 4 3 3 1 2 2 4 2 3 3 2 1 2 4 2 2**
Machine Group 1	1a 5a 5b 5c 11
Machine Group 2	1b 9a 9b 9c 20
Machine Group 3	7
Machine Group 4	1c 14a 14c 14b

5.2. Machine Encoding for Cell 2 and Formation of Cell 2 by GA

In order to avoid the complexities of the programming, the following machine numbers were programmed instead of the original numbers. Machines are encoded using MATLAB.

Table 6 shows the nomenclature of the machines. Machines are encoded with specific nomenclature using MATLAB programming. These encoded machines are used as input for Cell 2 formation.

Table 6. Machine Encoding for formation of Cell 2.

19a	**19b**	**19c**	**19d**	**18a**	**18b**	**18c**	**18d**	**16a**	**16b**	**16c**	**16d**	**17a**	**17b**	**17c**
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Figure 8 shows the formation of Cell 2. Cells are formed using the Genetic Algorithm (GA). In Cell 2, formation machines with similar functions are grouped into similar groups, as shown in the table below.

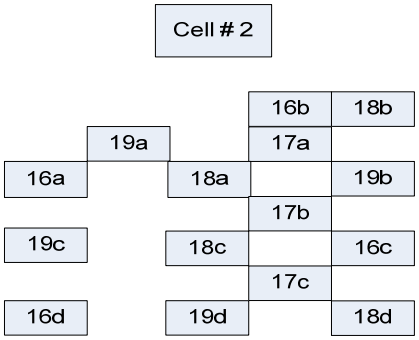

Figure 8. Formation of Cell 2.

Table 7 shows the machine chromosomes and intracell machine arrangements. Similar machines are located in a similar group based on their product and design functions.

Table 7. Machine Chromosome and arrangement of Machines in Cell 2.

Machine Chromosomes	**3 3 4 4 3 3 1 3 2 2 4 3 3 2 1 1 3 2 4**
Machine Group 1	19a 16a 19c 16d
Machine Group 2	19a 18a 18c 19d
Machine Group 3	16b 17a 17b 17c
Machine Group 4	18b 19b 16c 18d

5.3. Machine Encoding for Cell 3 and Formation of Cell 3 by GA

Table 8 shows that the machines are encoded first, and then these encoded machines are used as input for the formation of Cell 3.

Table 8. Machine Encoding for Formation of Cell 3.

19a	**19b**	**8a**	**8b**	**8c**	**2a**	**2b**	**17**	**15a**	**15b**	**18**	**3**	**11**	**6**	**12**
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Figure 9 shows the formation of Cell 2. Cells are formed using the Genetic Algorithm (GA). In Cell 3 formation, machines with similar functions are grouped into similar groups, as shown in the table below.

Cell # 3		
3	15a	6
2a	15b	8a
2b	18	8b
19b	19a	17
12	11	13

Figure 9. Formation of Cell 3.

Table 9 shows the machine chromosomes and intracell machine arrangements. Similar machines are located in a similar group based on their product and design functions.

Table 9. Machine Chromosome and arrangement of Machines in Cell 3.

Machine Chromosomes	**2 3 2 4 3 3 1 4 2 4 2 3 3 2 1 2 4 4 3**
Machine Group 1	3 2a 2b 19b 12
Machine Group 2	15a 15b 18 19a 11
Machine Group 3	6 8a 8b 17 13

5.4. Machine Encoding for Cell 4 and Formation of Cell 4 by GA

Table 10 shows the nomenclature of the machines. Machines are encoded with specific numbers using MATLAB programming. These encoded machines are used as input for the formation of Cell 4.

Table 10. Machine Encoding for formation of Cell 4.

3a	**3b**	**4c**	**4 a**	**4b**	**4 c**	**7a**	**7 b**	**11a**	**11b**	**8c**	**8 a**	**8b**	**7c**	**8c**
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Figure 4 shows the formation of Cell 4. Cells are formed using the Genetic Algorithm (GA). In Cell 11, formations of machines with similar functions are grouped into similar group, as shown in the table below.

Table 11 and Figure 10 show the machine chromosomes and intracell machine arrangements. Similar machines are located in a similar group based on their product and design functions.

Table 11. Machine Chromosome and arrangement of Machines in Cell 4.

Machine Chromosomes	4 4 3 4 3 3 1 2 2 4 2 2 3 2 1 2 4 3 3
Machine Group 1	8b
Machine Group 2	7b 4b 4c 3a
Machine Group 3	3b 11b 7c 4a
Machine Group 4	8c 11c 7a
Machine Group 5	4c 11a 8a

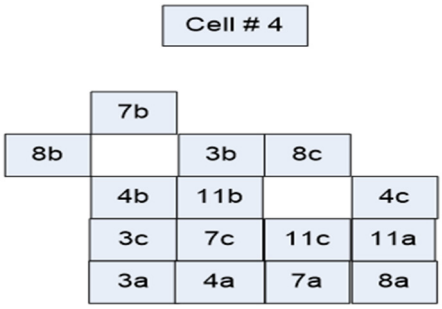

Figure 10. Formation of Cell 4.

5.5. Machine Encoding for Cell 5 and Formation of Cell 5 by GA

Table 12 shows the nomenclature of machines, while Table 13 represents machine chromosome and arrangement. Machines are encoded with specific numbers using MATLAB programming. These encoded machines are used as input for the formation Cell 5.

Table 12. Machine Encoding for formation of Cell 5.

13a	13b	15c	13d	6a	6b	6c	10a	10b	2a	2b	2c	2d	15a	15d
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 13. Machine Chromosome and arrangement of Machines in Cell 5.

Machine Chromosomes	1 1 3 4 3 3 4 2 2 4 2 3 3 2 1 2 4 2 2
Machine Group 1	13a 13c 15c
Machine Group 2	10a 10b 2c
Machine Group 3	2d 6a 6b 6c
Machine Group 4	6d 2a 13b 2b
Machine Group 5	13d
Machine Group 6	15d 15a 15c

Figure 11 shows the formation of Cell 5. Cells are formed using the Genetic Algorithm (GA). In Cell 5, formations of machines with similar functions are grouped into similar groups, as shown in the table below.

Table 14 shows the results' evaluation. Each machine's utilization and flexibility are shown in Section 1 of the table. Cell Formation utilization and flexibility are shown in Section 2 of the table. System utilization and flexibility are shown in Section 3.

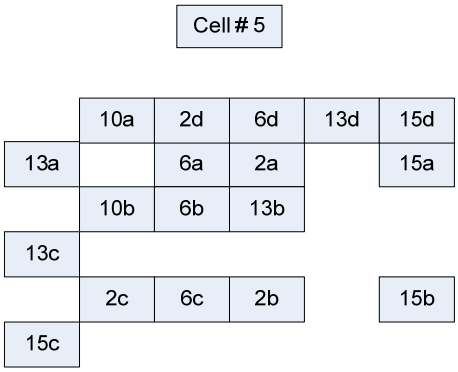

Figure 11. Formation of Cell 5.

Table 14. Results Evaluation.

Machine			Cell Formation			System	
Machine No.	**Utilization**	**Flexibility**	**Cell Formation**	**Utilization**	**Flexibility**	**Productivity**	**Flexibility**
1	0.4222	0	Cell 1	0.5809	0.0547	0.0885	0.1466
2	0.2435	0	Cell 2	0.4867	0.2457		
3	0.1166	0.6534	Cell 3	0.3722	0.1854		
4	0.5644	0	Cell 4	0.6789	0.2377		
5	0.8633	0.5878	Cell 5	0.8422	0.2244		
6	0.2366	0.4932					
7	0.1722	0					
8	0.9344	0					
9	0.6788	0.8124					
10	0.1635	0.3544					
11	0.3577	0					
12	0.8511	0.1268					
13	0.6633	0					
14	0.9244	0					
15	0.4446	0.2541					

5.6. Comparison of Performance of Cell Formation Efficiency with Other Methods

Ten problems chosen from the literature are used to test the algorithm's performance. The problem size varies from "5 machines × 7 parts" to "20 machines × 20 parts". The results from earlier reports are compared with the solution obtained for these problems based on the efficiency of Cell Formation (grouping). The method is run multiple times using the given parameters in order to guarantee a high-quality solution. There are ten runs by default. The part machine incidence matrix is related to the parameters that affect the quality of the solution. A matrix might not be well-structured, making it difficult to classify with optimal effectiveness. The problem size is another consideration. It takes a lot of runs and iterations (generations) to solve an unstructured large-sized problem. These variables determine the number of runs and algorithm parameters. The comparison of Cell Formation (grouping) efficiency is carried out with grouping efficiency (GE) by the following five methods, and the methods were chosen based on the literature: clustering algorithm [38], Genetic Algorithm [39], hybrid algorithm [40], genetic programming [41], and evolutionary algorithm [42].

Data set problems 1–4, 6, 7, 9, and 10 are taken from Gonclaves and Resende [42], data set problem 5 from Chandrasekharan and Rajagopalan [43], and data set problem 8 from Tariq, Hussain, and Ghafoor [40]. The group efficiency (GE) of the above methods is taken from [40,42,43]. The problem magnitude, their sources, and the outcomes are displayed in Table 4. Following the completion of the 10 issues, it was discovered that, for the most part, a superior configuration based on GE could be achieved. The results are listed below:

Total number of problem sets—10.
Problem sets with improvements—9 (70%).
Maximum improvement of GE—8.85 (problem 4).
Average improvement of 7 problems—4.9.
Number of problems without improvement—1.

It is obvious that regardless of the size of the problem, better results are attained.

This is particularly conspicuous when the data in an ill-structured part machine incidence matrix are difficult to aggregate. The suggested method provides the ideal solution for the ideal problems listed in the literature, when the GE of one is feasible. Most approaches yield the best results when used for ideal or nearly ideal problems, when grouping with a minimal number of exceptional parts and voids is possible. However, those models do not work well with input data that are not organized. In this regard, the suggested algorithm performs fairly well. In this approach, the novel GA based on machine encoding is crucial to obtaining better solutions.

6. Conclusions

Though there has been a lot of research on CMS design issues, there have been few studies on taking Cell Formation and a dynamic flexible architecture into consideration. This study created a novel method that uses a number of flexibility parameters to direct the formation of cells. The proposed method was created to address complex, multiobjective design problems in CMS on a big scale. It incorporated a Genetic Algorithm (GA), an encoding function technique, and machine layout cell designs that maximize performance outcomes in order to obtain Cell Formation. The machines and their components were introduced as a matrix. In GA runs, a number of chromosomal evolution and selection throughput adjustment techniques were used. In order to determine the best Cell Formation and machine layout, Genetic Algorithms (GAs) were used. The machines were programmed for each Cell Formation. This approach is distinctive in a number of ways, particularly when flexibility is viewed as an expression of the trade-off between machine usage and the number of exceptional features, i.e., in terms of Cell Formation dimensions Cell Formation based on any required flexibility ranging from 0.1 to 0.8, resolving issues in real-world case studies. The effectiveness of the established approach was demonstrated through the resolution of a Pakistani automotive real-world case study. It is concluded that the proposed GA based on the machine encoding technique optimizes the design of CMS and improves the group efficiency to 72.81 (average value) compared with other metaheuristics algorithms, as shown in Table 15.

Table 15. Performance metric group efficiency comparison with other methods.

Problem Set	Problem Size (M × P)	Clustering Algorithm (M.ST)	Genetic Algorithm (GA)	Hybrid Algorithm (HA)	Genetic Programming (GP)	Evolutionary Algorithm (EA)	Proposed Algorithm
1	5 × 7	-	-	73.68	-	73.68	**74.58**
2	6 × 8	-	76.92	76.92	-	76.92	**79.44**
3	7 × 11	-	46.88	53.13	-	53.13	**61.95**
4	8 ×12	-	-	68.3	-	68.3	68.56
5	8 × 20	58.72	58.32	58.70	58.33	-	**59.45**
6	10 × 10	70.59	70.59	70.59	-	70.59	**74.33**
7	10 × 15	91.00	91.00	92.00	91.00	92.00	89.56
8	10 × 20	-	-	-	-	90.00	90.23
9	14 × 24	-	67.44	70.50	-	69.33	**78.60**
10	20 × 20	-	37.12	42.96	-	43.20	**51.45**

Additionally, it would be beneficial to investigate whether the current production processes can accommodate a new part throughout cell manufacturing operations. When admitting additional parts, logistics and cell reorganization costs should be taken into

account in the objective functions, and a new strategy should be designed to deal with the optimization model's high level of complexity.

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References

1. Adinarayanan, A.; Dinesh, S.; Balaji, D.S.; Umanath, K. Design of machine cell in cellular manufacturing systems using PSO approach. In *Materials Today: Proceedings*; Elsevier: Amsterdam, The Netherlands, 2021; Volume 46, Part 9; pp. 3951–3955, ISSN 2214-7853.
2. Nayak, N.C.; Ray, P.K. Flexibility and performance relationships: Evidence from Indian bearing manufacturing firm. *Int. J. Model. Oper. Manag.* **2010**, *1*, 67–83. [CrossRef]
3. Imran, M.; Kang, C.; Lee, Y.H.; Jahanzaib, M.; Aziz, H. Cell formation in a cellular manufacturing system using simulation integrated hybrid genetic algorithm. *Comput. Ind. Eng.* **2017**, *105*, 123–135. [CrossRef]
4. Rafiee, K.; Rabbani, M.; Rafiei, H.; Rahimi-Vahed, A. A new approach towards integrated cell formation and inventory lot sizing in an unreliable cellular manufacturing system. *Appl. Math. Model.* **2011**, *35*, 1810–1819. [CrossRef]
5. Ariafar, S. Inter-Cell and Intra-Cell Facility Layout Models under Different Demand Environments in Cellular Manufacturing Systems. Ph.D. Thesis, Universiti Putra Malaysia, Seri Kembangan, Malaysia, 2012.
6. Mejía-Moncayo, C.; Battaia, O. A hybrid optimization algorithm with genetic and bacterial operators for the design of cellular manufacturing systems. *IFAC-PapersOnLine* **2019**, *52*, 1409–1414. [CrossRef]
7. Sakran, H.K.; Mahbuba, H.M.; Jafer, A.S. A review of a basic concept of cellular manufacturing. *Int. J. Des. Manuf. Technol.* **2016**, *8*, 30–37. [CrossRef]
8. Lokesh, K.; Jain, P. Dynamic Cellular Manufacturing Systems Design—A Comprehensive Model & Hhga. *Adv. Prod. Eng. Manag.* **2010**, *5*, 151–162.
9. Raminfar, R.; Zulkifli, N.; Vasili, M. A mathematical programming model for cell formation problem with machine replication. *J. Appl. Math.* **2013**, *2013*, 285759. [CrossRef]
10. Papaioannou, G.; Wilson, J.M. The evolution of cell formation problem methodologies based on recent studies (1997–2008): Review and directions for future research. *Eur. J. Oper. Res.* **2010**, *206*, 509–521. [CrossRef]
11. Ariafar, S.; Ismail, N. An improved algorithm for layout design in cellular manufacturing systems. *J. Manuf. Syst.* **2009**, *28*, 132–139. [CrossRef]
12. Ripon, K.S.; Glette, K.; Mirmotahari, O.; Høvin, M.; Tørresen, J. Pareto optimal based evolutionary approach for solving multi-objective facility layout problem. In *Proceedings of the Neural Information Processing: 16th International Conference, ICONIP 2009, Part II 16, Bangkok, Thailand, 1–5 December 2009*; Springer: Berlin/Heidelberg, Germany, 2009.
13. Chang, C.-C.; Wu, T.-H.; Wu, C.-W. An efficient approach to determine cell formation, cell layout and intracellular machine sequence in cellular manufacturing systems. *Comput. Ind. Eng.* **2013**, *66*, 438–450. [CrossRef]
14. Hazarika, M.; Laha, D. Genetic algorithm approach for machine cell formation with alternative routings. *Mater. Today Proc.* **2018**, *5*, 1766–1775. [CrossRef]
15. Pradhan, T.; Mishra, S.R. Implementation of machine part cell formation algorithm in cellular manufacturing technology using neural networks. *Int. J. Hybrid Inf. Technol.* **2015**, *8*, 173–178. [CrossRef]
16. Hameri, A.-P. Production flow analysis—Cases from manufacturing and service industry. *Int. J. Prod. Econ.* **2011**, *129*, 233–241. [CrossRef]
17. Vakharia, A.J.; Wemmerlöv, U. A comparative investigation of hierarchical clustering techniques and dissimilarity measures applied to the cell formation problem. *J. Oper. Manag.* **1995**, *13*, 117–138. [CrossRef]
18. Caux, C.; Bruniaux, R.; Pierreval, H. Cell formation with alternative process plans and machine capacity constraints: A new combined approach. *Int. J. Prod. Econ.* **2000**, *64*, 279–284. [CrossRef]
19. Ghosh, T.; Dan, P.K. An effective machine-part grouping algorithm to construct manufacturing cells. *arXiv* **2012**, arXiv:1212.5265.

20. Ghosh, T.; Doloi, B.; Dan, P.K. Utilization-based grouping efficiency and multi-criteria decision approach in designing of manufacturing cells. *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.* **2017**, *231*, 505–522. [CrossRef]
21. Schaller, J. Designing and redesigning cellular manufacturing systems to handle demand changes. *Comput. Ind. Eng.* **2007**, *53*, 478–490. [CrossRef]
22. Dalfard, V.M. New mathematical model for problem of dynamic cell formation based on number and average length of intra and intercellular movements. *Appl. Math. Model.* **2013**, *37*, 1884–1896. [CrossRef]
23. Bagheri, M.; Bashiri, M. A new mathematical model towards the integration of cell formation with operator assignment and inter-cell layout problems in a dynamic environment. *Appl. Math. Model.* **2014**, *38*, 1237–1254. [CrossRef]
24. Satoglu, S.I.; Suresh, N.C. A goal-programming approach for design of hybrid cellular manufacturing systems in dual resource constrained environments. *Comput. Ind. Eng.* **2009**, *56*, 560–575. [CrossRef]
25. Dimopoulos, C.; Zalzala, A.M. Recent developments in evolutionary computation for manufacturing optimization: Problems, solutions, and comparisons. *IEEE Trans. Evol. Comput.* **2000**, *4*, 93–113. [CrossRef]
26. Martins, I.C.; Pinheiro, R.G.; Protti, F.; Ochi, L.S. A hybrid iterated local search and variable neighborhood descent heuristic applied to the cell formation problem. *Expert Syst. Appl.* **2015**, *42*, 8947–8955. [CrossRef]
27. Chung, S.-H.; Wu, T.-H.; Chang, C.-C. An efficient tabu search algorithm to the cell formation problem with alternative routings and machine reliability considerations. *Comput. Ind. Eng.* **2011**, *60*, 7–15. [CrossRef]
28. Gonçalves Filho, E.V.; Tiberti, A.J. A group genetic algorithm for the machine cell formation problem. *Int. J. Prod. Econ.* **2006**, *102*, 1–21. [CrossRef]
29. Deep, K.; Singh, P.K. Design of robust cellular manufacturing system for dynamic part population considering multiple processing routes using genetic algorithm. *J. Manuf. Syst.* **2015**, *35*, 155–163. [CrossRef]
30. Rezazadeh, H.; Khiali-Miab, A. A two-layer genetic algorithm for the design of reliable cellular manufacturing systems. *Int. J. Ind. Eng. Comput.* **2017**, *8*, 315–332. [CrossRef]
31. Modrak, V.; Pandian, R.S.; Semanco, P. Calibration of GA parameters for layout design optimization problems using design of experiments. *Appl. Sci.* **2021**, *11*, 6940. [CrossRef]
32. Jerin Leno, I.; Sankar, S.S.; Ponnambalam, S. Integrated layout design approach for cellular manufacturing system. In *Proceedings of the International Conference on Intelligent Robotics, Automation, and Manufacturing, Kuala Lumpur, Malaysia, 28–30 November 2012*; Springer: Berlin/Heidelberg, Germany, 2012.
33. Chandrasekar, K.; Venkumar, P. Genetic algorithm approach for integrating cell formation with machine layout and cell layout. *Int. J. Oper. Res.* **2013**, *16*, 155–171. [CrossRef]
34. Forghani, K.; Mohammadi, M. A genetic algorithm for solving integrated cell formation and layout problem considering alternative routings and machine capacities. *Sci. Iran.* **2014**, *21*, 2326–2346.
35. YounesSinaki, R.; Sadeghi, A.; Mosadegh, H.; Almasarwah, N.; Suer, G. Cellular manufacturing design 1996–2021: A review and introduction to applications of Industry 4.0. *Int. J. Prod. Res.* **2023**, *61*, 5585–5636. [CrossRef]
36. Mansour, H.; Afefy, I.H.; Taha, S.M. Heuristic-based approach to solve layout design and workers' assignment problem in the cellular manufacturing system. *Int. J. Manag. Sci. Eng. Manag.* **2022**, *17*, 49–65. [CrossRef]
37. Liu, Q.; Ullah, S.; Zhang, C. An improved genetic algorithm for robust permutation flowshop scheduling. *Int. J. Adv. Manuf. Technol.* **2011**, *56*, 345–354. [CrossRef]
38. Srinivasan, G. A clustering algorithm for machine cell formation in group technology using minimum spanning trees. *Int. J. Prod. Res.* **1994**, *32*, 2149–2158. [CrossRef]
39. Cheng, C.; Gupta, Y.; Lee, W.; Wong, K. A TSP-based heuristic for forming machine groups and part families. *Int. J. Prod. Res.* **1998**, *36*, 1325–1337. [CrossRef]
40. Tariq, A.; Hussain, I.; Ghafoor, A. A hybrid genetic algorithm for machine-part grouping. *Comput. Ind. Eng.* **2009**, *56*, 347–356. [CrossRef]
41. Dimopoulos, C.; Mort, N. A hierarchical clustering methodology based on genetic programming for the solution of simple cell-formation problems. *Int. J. Prod. Res.* **2001**, *39*, 1–19. [CrossRef]
42. Tunnukij, T.; Hicks, C. An enhanced grouping genetic algorithm for solving the cell formation problem. *Int. J. Prod. Res.* **2009**, *47*, 1989–2007. [CrossRef]
43. Chandrasekharan, M.P.; Rajagopalan, R. An ideal seed non-hierarchical clustering algorithm for cellular manufacturing. *Int. J. Prod. Res.* **1986**, *24*, 451–463. [CrossRef]