Human cognition inspired procedures for part family formation based on novel Inspection Based Clustering approach

Naga Sai R. Gopisetti [1a], Maria Leonilde R. Varela [2b] J. Machado [3c*]

1School of Engineering, Edith Cowan University, Joondalup, Perth, Western Australia, Australia

[a]sairam27@hotmail.com

2Department of Production and Systems, School of Engineering, University of Minho, Algoritmi Research Centre, Guimarães, Portugal.

[b]leonilde@dps.uminho.pt

3Department of Mechanical Engineering, School of Engineering, University of Minho, MEtRICs Research Centre, Guimarães, Portugal.

[c]jmachado@dem.uminho.pt

Received: DD/MM/AA – Reviewed: DD/MM/AA -- Accepted: DD/MM/AA - DOI: https://dx.doi.org/10.6036 (To be completed by Editor)

ABSTRACT:

Human cognition based procedures are promising approaches for solving different kind or problems, and in this paper is addressed the part family formation problem based on a human cognition inspired procedure through a graph-based approach, based on pattern recognition. There are many algorithms which consider nature inspired models for solving a broad range of problem types. However, there is a noticeable existence of a gap in implementing cognitive kind of models based on human cognition, which are generally characterized by "visual thinking", rather than complex mathematical models. Hence, the natural power of reasoning by detecting the patterns by human cognition is used in this study. This paper closes the gap of employing the human cognition through the partial implementation of graph theory to model and solve the grouping part machine problems of any size. Results obtained have shown that most of the problems solved by using the proposed approach have provided interesting benchmark results when compared with previous results given by GRASP(Greedy Randomized Adaptive Search Procedure) heuristics

Keywords: Cellular manufacturing systems; part family formation; human cognition; inspection-based clustering.

1. - INTRODUCTION

The importance of enabling agile manufacturing solutions for producing customized products with reduced amount of time spent on manufacturing systems reconfiguration is a fundamental improvement factor in production systems. Thus, the systematic assembly of groups of machines dedicated to produce a set of parts is upmost importance in the context of cellular manufacturing systems (CMS) problems solving. The CMS problems are usually represented as 2D matrices with parts on top and machines on sides followed by process or operations marked typically as one with respect to part and machine. The voids or non-operational elements are represented by 0. Exceptions are those which fall outside of a group which may need additional machines to process the parts. The main goal of solving these problems is to reduce or isolate maximum number of exceptions. Therefore, all the methods try to reduce or isolate these exceptions. In addition, as the methods to solve these problems get complicated when the input matrix size gets increases, computers have to be used to solve such large problems alongside with evaluating a set of performance parameters, including computation time, time complexity, as these problems usually are NP-hard. The following study introduces a special kind of algorithms, which solves these NP hard problems based on the recognition of patterns without any mathematical quantification. It is also proved that, these algorithms are efficient in handling the sparse matrix and yield optimised results by minimising the number of voids in the cells.

MACHINES \ PARTS	A	B	C	D	E
1	1	1	0	0	0
2	1	1	0	0	0
3	0	0	1	1	1
4	0	0	1	1	1

A1

MACHINES \ PARTS	A	B	C	D	E
1	1	1	0	1	0
2	1	0	0	0	0
3	0	1	1	0	1
4	0	0	1	1	1

A2

Figure 1 : The ideal part-family problem representation in 2D matrix with A1 showing the ideal matrix and A2 showing the real-world problem with exceptions

Figure 1 depicts a generic kind of problem representation which are usually solved as binary problems. The binary problems are those with the operations and voids being placed side by side and this pattern continues until the size bound of the problem, and the minimum size for this problem should be more than three.

There are various algorithms formulated by considering the mathematical description of modelling the nature and artificial intelligence with aim of bringing the optimum grouping for any given problem. In addition, there are multiple methods which are classified according to the methodologies such as descriptive methods, cluster analysis, graph partition principles, along with mathematical programming and more recently artificial intelligence-based approaches as discussed and reviewed by many authors, for instance by Papaioannou & Wilson (2010); Selim, Askin, & Vakharia (1998), among others, as will be further detailed next. Although, since the method proposed in the current study belongs to evolutionary algorithm (EA) type, a particular focus on more or less closely related approaches were considered for the state of art contextualization.

There are some initial studies on grouping problems by application of artificial intelligence and the first paper which described the use of domain specific acquaintance rules and modelling system to automate the process of identifying the parts to their respective cell was put forward by Elmaraghy and Gu (Elmaraghy & Gu, 1989). The application of neural networks for solving Cellular Manufacturing Problems (CMS) was discussed (Rao & Gu, 1995) and this had laid to a fundamental objective for use of variant neural networks and fuzzy methodologies. The pure utilisation of ART1 networks to solve the clustering problem was first proposed and used and remind as initial benchmark procedure in (Dagli & Huggahalli, 1995). The use of Hopefield neural networks in combination with objective guided search to solve the CMS problems was described where this approach needs no initial training to detect the cells in any given problem and even handles the tailback problems (Zolfagha Ri & Liang, 1997). Various cell quality parameters have been used to devise and guide a neural network to find the global optimum for any given CMS problems (Liang & Zolfaghari, 1999). Two neural networks -Hopefield and Potts means - had been used by means of minimising the transportation cost, which proved to work better and faster in comparison with another algorithm (Lozano, Canca, Guerrero, & Garcıa, 2001). The influence of size of the Cell Formation problem (CF) on viability and strength of the networks was studied and tested on various benchmarked problems and shown a reliable dependency for maximum optimality (Solimanpur, Vrat, & Shankar, 2004). A parameter based neural network in ART1 configuration was used to find the cells in the given problems and stood to be an interesting approach for minimising the exceptional elements (Venkumar & Haq, 2005). In the following year, they had produced another work with the application of Kohonen self-organising map neural networks which did work efficiently in conjunction to previous method (Venkumar & Haq, 2006). The modified approach from Dagli and Hugganhalli (Dagli & Huggahalli, 1995) was used to formulate a new neural network by reliable selection of vigilance parameters, which had proved the efficiency of various problems published in many other works (Yang & Yang, 2008). The application of resonance theory by accounting the various cell parameters such as operation time, sequences and lost sizes was studied and proposed as a new performance measure for a given methodology in (Sudhakara Pandian & Mahapatra, 2009). By coupling Genetic algorithm and ANN, (Rezaeian, Javadian, Tavakkoli-Moghaddam, & Jolai, 2011) has used to solve the CMS problems where the method proposed had outperformed the simulated annealing method for deriving the optimum solutions. From this year, most of the interest had paved to the implementation of heuristics and different types of evolutionary algorithms for solving CMS problems.

There are tremendous implementations of genetic algorithm along with its modified co-variants in solving the CMS problems (Renzi, Leali, Cavazzuti, & Andrisano, 2014), from the first studies (Venugopal & Narendran, 1992b), to prove its significance in lending optimal solutions by minimising the cell moments (Joines, Culbreth, & King, 1996; Onwubolu & Mutingi, 2001). A Binary-objected (Abbasi, Shadrokh, & Arkat, 2006) and multi-objective (Neto & Gonçalves Filho, 2010) approach by implementing Genetic algorithm for minimisation of common objectives such as number of exceptions and void was proposed. Ant colony optimisation was inspired from the foraging activity of the ants and this process was mimicked to solve the CF problems (Attila Islier*, 2005; Dorigo, Caro, & Gambardella, 1999; Prabhaharan, Asokan, Girish, & Muruganandam, 2005) which have shown a successful dominance over other available best performing approaches. Particle swarm optimisation (PSO) is another kind of approach which was derived from the flocking nature of birds. This was achieved through evaluation of best particles and by comparing it with other best possible particles and then imitate their nature until the target is achieved. The objective of minimising the inter and intra cell movements in CF problems by application of PSO was proved to give optimal and near optimal solutions but restricted to small datasets (Andres & Lozano, 2006) and the modified approach (Durán, Rodriguez, & Consalter, 2008) from the previous was made by introducing the measure of likelihood to find the solutions for most of the problems. Another type of meta-heuristic was called as simulated annealing (SA), which was inspired by the annealing process of metals (Varela, & Ribeiro, 2003). By carful observation in the change in probability of objective function the acceptance and rejection of the generated solution was made (Metropolis, Rosenbluth, Rosenbluth, Teller, & Teller, 1953). The first study to approach the CF problems in the SA process had shown the possible leverage in efficacy of the benchmarked problems (Wu, Chang, & Chung, 2008). There are many variants by turning down various parameters to obtain better and efficient solutions (Arkat, Saidi, & Abbasi, 2007; Sridhar & Rajendran, 1993; Vakharia & Chang, 1990; Venugopal & Narendran, 1992a; Xambre & Vilarinho, 2003). The new EA was proposed based on the firefly to reorganise themselves into moving clusters, this same methodology was used to solve the CF problems (Sayadi, Hafezalkotob, & Naini, 2013) and now gaining more interest to adapt to more variant problems. Other kind of current methods share the use of the network, for instance social network analysis as described in Varela et al (2016, 2020), where similar problem and underlying constraints are focused, and which has also revealed to be an appropriate approach to solve industrial plant layout problems. Moreover, other kind of approaches have been used, for instance for dealing with human centred approaches for plant layout analysis, for instance based on MAS and further combination with Meta-Heuristics, as can be seen in Alves et al (2019), in which a Hybrid System for Simultaneously Supporting Scheduling and Plant Layout Adjustment is put forward.

In 2017 Zupan, et al. propose a combination of Schmigalla modified triangular method and the Schwerdfeger circular process to design clusters of products on the basis of a product line data and determine an ideal layout optimization on the basis of the intensity of material flow. Their method was applied to a cluster of 20 similar orders in design and technology that were processed at 10 workplaces, which did enable them to propose a transition from a O-cell to a U-cell.

Further, in 2017, also Pan et al did review modelling and scheduling methods about cluster tools including nonrevisiting and revisiting processes, along with a set of constraints, and a comparative analysis is also included by the authors.

Laha, and Hazarika (2017) propose a heuristic approach based on Euclidean Distance matrixes to identify part families and machine cells in order to minimize the intercellular movement and to maximize the machine utilization within a cell.

The authors did perform computational experiments by using 20 benchmark problem sets taken from the literature, and they concluded that their proposed heuristic is competitive regarding other well-known existing algorithms in terms of grouping efficacy.

Ostrosi, and Fougères (2018) propose an approach to address intelligent virtual manufacturing cell formation in cloud based design for cellular manufacturing by using the concepts of the holon and the attractor, integrating the uncertainty in the modelling of part design and part–manufacturing network. Through their approach intelligent manufacturing features, modelled as fuzzy agents, are recognized in CAD part models and the distributed capabilities of machines in cloud manufacturing are evaluated through mobile intelligent agents. Moreover, intelligent virtual manufacturing cells, with holonic structure, emerge from the interactions of fuzzy machine holon agents and fuzzy part holon agents with holon agent attractors. According to the authors, the concepts of the holon and the attractor allow multi-scale cell formation with holonic structure: *"intelligent virtual manufacturing cells within an intelligent virtual manufacturing cell"*, and these fuzzy cell holons overcome the distinction continuous–discontinuous of traditional cell design formation problem.

In 2019, Eliguzel, and Ozceylan considered a gym centre with 33 sport equipment (machines) and 10 activity program (parts) to study the location of the equipment for each program to use the layout efficiently and decrease the distance between machines through a three-phased solution approach based on two clustering methods, namely rank ordering clustering (ROC) and average linkage clustering (ALC), and the authors state that through their proposed approach it was possible to increase the space utilization and to decrease the distance between machines in the considered gym centre.

Prasad, and Jayswal (2019) put forward a methodology to facilitate reconfiguration in the manufacturing system. Their proposed methodology includes the calculation of similarity matrix, formation of part family, and selection of part family, by using ALC algorithm for part family formation and three criteria for the selection of part family about reconfiguration effort, under-utilization cost, and floor space cost. Moreover, the AHP method has been used to calculate the weights, along with a method for the selection of alternatives. The authors conclude that in the manufacturing system, machines should be grouped on the basis of reconfiguration cost.

Danilovic, and Ilic, in 2019, proposed to design an algorithm for the cell formation problem that could be more efficient that other best-known algorithms for the same problem considered. According to the authors, their strategy underlying their proposal consists on using specificities of the input instances to narrow down a feasible set, and thus increase the efficiency of the optimization process.

As a result, the authors did put forward an extensible hybrid algorithm that can be used to solve complex, multi-criteria optimization cell formation problems. As stated by the authors, their proposed algorithm did enable to produce solutions that are as good as, or better than, the best results previously reported in literature on all commonly used test instances. Moreover, they refer that the time efficiency of their proposed algorithm is at least an order of magnitude better than the efficiency of the most efficient reported algorithms. Thus, through their results obtained they were able to conclude that the modularity and generality of their proposed algorithm imply a significant impact on the expert systems for cell formation problem since their proposed strategy is able to improve the efficiency of existing algorithms for the grouping problems.

Bortolini, Galizia, and Mora, in 2019, did also propose another approach to design and to manage Cellular Reconfigurable Manufacturing Systems from a multi-product and multi-period perspective. In their work they did consider multiple cells of machines equipped with Reconfigurable Machine Tools made of basic and auxiliary custom modules to perform specific tasks. In their approach the authors did consider two steps, the first one about the machine cell design phase to assign machines to cells, and second one consisting on the cell loading phase, to assign modules to each machine and cell. The goal of their proposed approach consists on

guaranteeing an economic sustainability of the manufacturing system by exploring how to best balance the part flow among machines already equipped with the required modules and the effort to install the necessary modules on the machine on which the part is located. Nalluri, et al. (2019) studied a clonal selection algorithm (CSA) that uses a new affinity function and part assignment heuristic for solving a multi-objective cell formation problem. Their proposed CSA has been hybridized with genetic algorithm for generating feasible cell sequences that fulfil both mutual exhaustively and exclusion properties of machine cells prior to the initial population generation. Additionally, the authors have built a new part assignment heuristic function that maps parts to machine cells and a basic affinity function into their proposed CSA so that it can act as the utility function to solve the multi-objective cell formation problem. Their hybrid CSA (HCSA) has been analysed through a set of 52 benchmark instances collected from the literature, and according to the authors their obtained results did demonstrate that their proposed HCSA is promising in comparison with existing approaches available in recent literature.
Recently, Rajesh, Gupta, and Rajendran (2020) aimed to demystify the possibility of using Hamann, Yule (value ranges from -1 to +1), and Jaccard (value ranges from 0 to +1) similarity measures for the machine-part cell formation (MPCF) by using the CARI heuristic that uses correlation coefficient (value ranges from -1 to +1) as the similarity measure. According to the authors, grouping efficacy achieved by CARI heuristic while using Hamann and Yule as similarity measure is less for 71.42% and 51% of the dataset respectively compared to the grouping efficacy achieved while using correlation coefficient as similarity measure.
Singh, and Singhal (2020) did also review the factors needed for improving productivity in the Indian manufacturing sector, by proposing an approach to find an alternative way to engage the material and workforce sources accessible in a plant, to contribute to the improvement of production and, subsequently, manufacturing productivity through the execution of a clustering technique with sequenced tooling to reach higher productivity.
Another interesting contribution is presented by Subramaniyan et al. (2020) propose a generic, unsupervised ML-based hierarchical clustering approach to detect throughput bottlenecks, which begins by generating a time series of a chosen bottleneck detection metric and then clusters the time series by using a dynamic time-wrapping measure and a complete-linkage agglomerative hierarchical clustering technique. Based on this approach, the authors were able to obtain clusters of machines with similar production dynamic profiles, revealed from the historical data that did enable the detection of bottlenecks. This approach proposed by the authors was demonstrated through two real-world production systems, and does integrate the concept of humans in-loop by using domain expert's knowledge.
However, the co-authors of this paper do believe that another kind of approach, based on the Human cognition may configure some important advantages besides existing ones, as currently very scarce human centred contributions are available, so an approach in this context is proposed in this paper for solving the CF problems, and will be briefly discussed in the following sections of this paper, which reflects the derivation of procedure from the natural or lively components. Thus, the remaining of this paper is organised as follows. Section 2 briefly describes the proposed approach for part family formation based on a human cognition inspired procedure through the IBC (Inspection Based Clustering) approach as described in this paper, along with the description of the case study carried out through this work. In section 3 main results achieved are shown and discussed, and finally, in section 4, main conclusions are presented, and some further directions about future work are pointed out.

2. PROPOSED APPROACH

The process of human learning is quite unique and interesting, it processes the instructions more visually and looks for the patterns to differentiate, recognise and predict the abstract information from any given context. This is like learning from the examples and deriving the conclusions for the process. In the current methodology, the same principle is used. By taking various problems which are solved using the traditional techniques, various patterns had been detected but only four of them were better suited to solve any kind of CF. As discussed above, there are four main patterns resolved in this study, and with one core formulation that supplements in each one to decide the hierarchy and sequence of the part and machine index to be updated. These patterns are converted to collection of algorithms with an interface called as IBC (Inspection based clustering), as shown in Figure 2. This interface allows users to interact with the solution and created using the C++ with WPF (Windows Presentation Framework) as the programming framework. The interface consists of three main areas being one called as INPUT matrix area where the problem is defined. This area is then split into two different tabs where the I/O (Input / Output) tables with respect to the part and machine are visualised, and which enable to assist the user to select the respective pattern suggestion given in the I/O tables and the main control panel where the algorithmic actions are coded into the buttons and the output matrix area where the solution is given. In addition, the total wall time is also given in the top corner of the interface which helps in calculation of the run time of the solution.

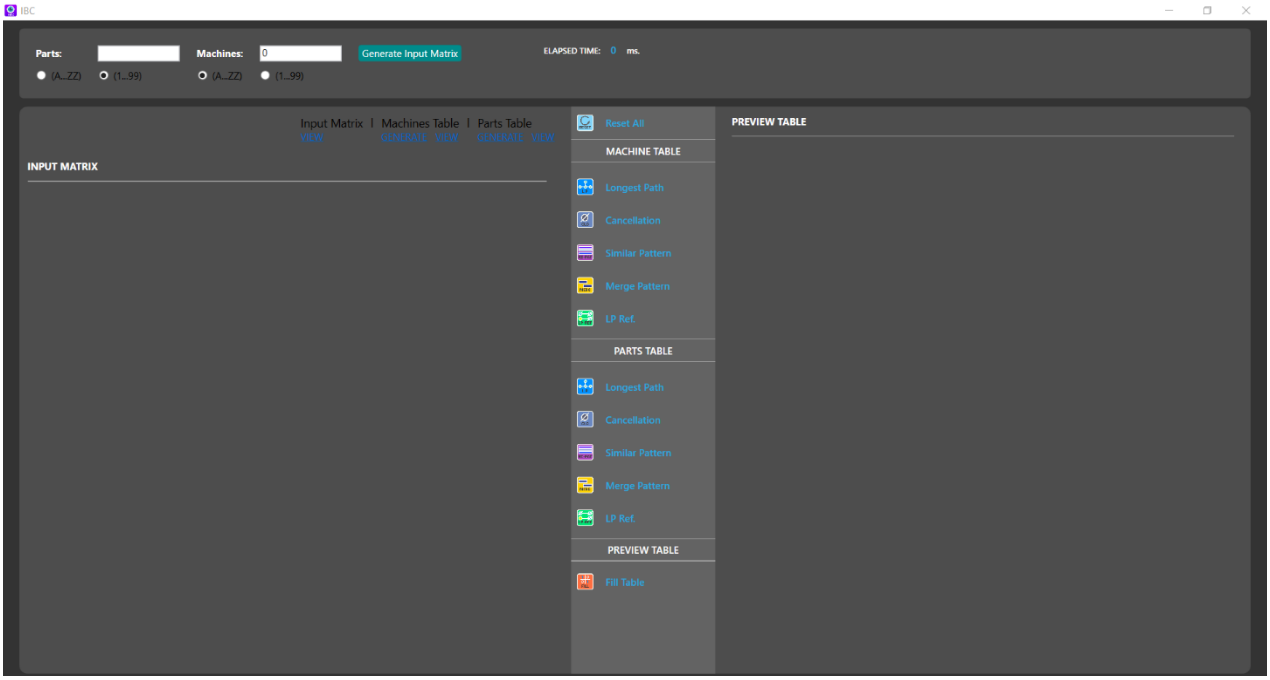

Figure 2: The user interface of the IBC and its features, and its panels that was made on WPF Platform

As specified above, very special tables are used in this tool called as I/O tables (Input and output tables) to detect the patterns from the input matrix. An I/O table is a simplified view of a complex graph which gives all the possible ways of the traversal of the machine through the parts and vice versa. Generally, the graph is directed with no weights or for the assumption the weights are assumed to be the unity. Through the graph parsing to the I/O tables, all the patterns are detected, which is suggested to the user with respect to the part or machine. This table generation also helps in the tedious manual checking and searching of the patterns. Moreover, this table generation is a basic step where it replaces the network topology into matrix form. A primitive example is given to demonstrate a sample I/O table generation in the following Figure 4 regarding the problem defined in the following section.

From the Figure 3, it is very evident that generation of I/O is interconnected with the input matrix data. However, it is more tedious to plot graphs for each problem as the size of the matrix is increased and the shape of the graph will be increased exponentially. Hence, the creation of networks was parsed into I/O as shown in Figure 4. The use of transit analogy in the graph is used which

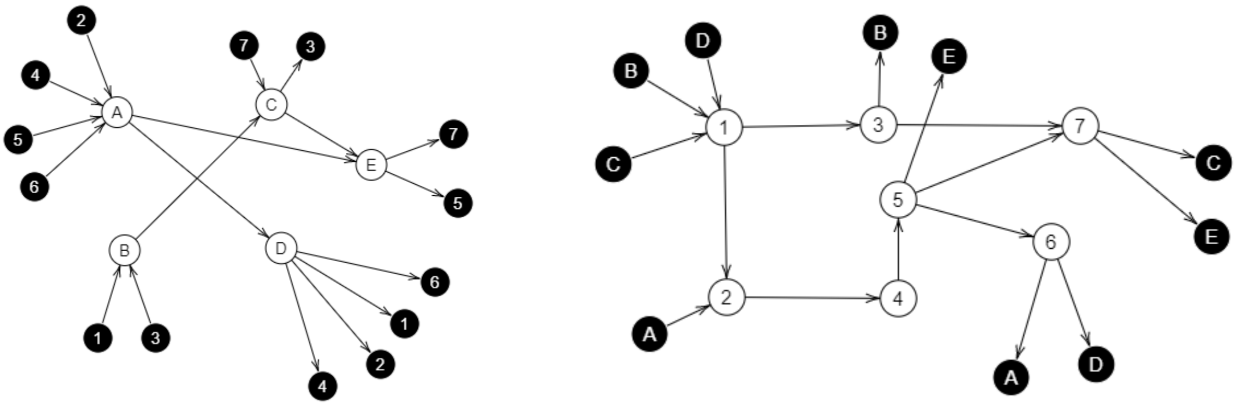

Figure 3: An example Network diagram of Part and Machine on transit analogy used.

As described in the figure 4 Input matrix it is assumed that the part will be travelling through the machines. This analogy was considered for the preserving the nature of algorithm. In general, the process of generation of the I/O table is made by iterating through the row and by keeping the columns index constant i.e. Machine node I/O table. For Instance, let us assume Part 1 is entering in Machine B, hence it is given as IN node and travelling through C which is given as intermediate nodes and exiting at D which is given as OUT node, likewise for Part 2, it is entering in Machine A and exiting at Machine D. Similarly, this process is applied to all nodes of Parts as an assumption that machine is transiting through all machines followed by part that is transiting through all the machines and the intermediate node visits are labelled as intermediate nodes.

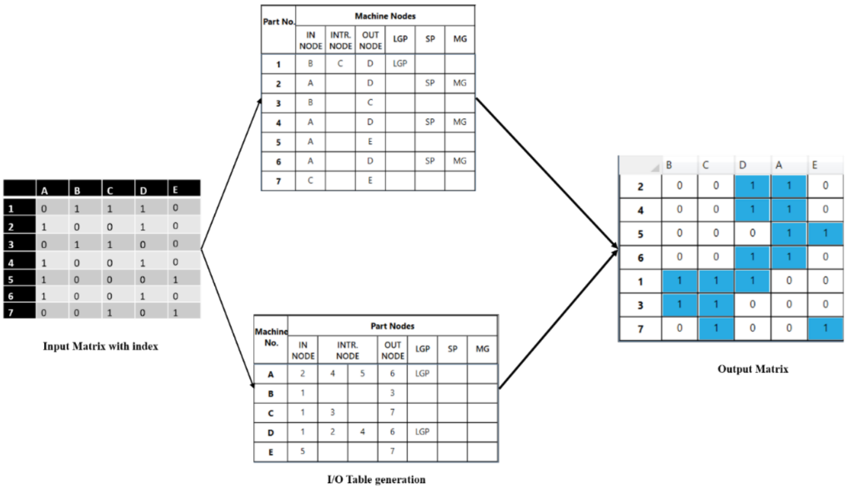

Figure 4: The Solution process implemented in IBC

As discussed in the above section, there are four main algorithms known as Longest path (LGP), Similar Pattern (SP), Merger (MG) and Longest path last Node Reference (LP.REF). The decision process is executed by auto cancellation based on the user input, where decisions are driven by the recognised patterns. If no patterns are detected, then user can use Cancellation method (CLC) to sequentially push all the generated index from the respected I/O tables into output Matrix area. These methods are automatically suggested by the interface without any human inference; however, the choice is based on the human requirements. The main drawback of this interface is that user cannot select a specific suggestion given by the interface, because the selection disturbs the hierarchy of previous nodes. The evaluation of all four algorithms are given as follows. It is noted that these algorithms are made unbiased to produce the block diagonalization of matrixes, it aims in identifying the sequential groups without possible collision with other cells.

Longest Path: As the algorithms are derived from the Network topology, the formation of longest path is one main pattern that exists in the graph. It helps in maximum node traversal in any given network and thereby increasing network coverage. As per the assumption, the weight of the given network is unity, forward pass technique is replaced by counting the number of the nodes for the all transits of machine or part. The I/O table parses the Input matrix in same way by enumerating the number of intermediate nodes for given part or machine index, and it suggests the user whether the detected pattern leads to longest part or to different pattern. However, there can exist more than one detected pattern for any given machine or part index and this leads the choice of selection and may affect the optimality of the solution. In most cases, the use of LGP is encouraged as it narrows the further selection by lowering the number of the nodes. The interface has set the internal logic to be greater than 3 as CF problems cannot be formulated with a 2 X 2 matrix. The minimum size of matrix needed to input is 4 x 4

Similar Pattern: This is a simple yet more powerful type of method for filtering the index of the problem very quickly. When there is a transit of two or more parts or machines through the same nodes along with the intermediate node in a same sequence, then the program detects this and will be termed as similar pattern. The motto of this algorithm is to eliminate the duplication or double transit of the machine or part node. If the size of matrix is too large, it had been observed that is a more chances of observing these patterns, at least more than twice and moreover, this algorithm in association with the LGP will yield good results as these both scrap the nodes very fast and effectively.

Cancelation: As discussed in above, cancellation of machine and nodes is core of all predominant algorithms formulated and of very primitive type. It has two advantages; one is if no patterns are detected then this algorithm pushes all the respected element in sequence generated by the I/O tables into the solution matrix and other is, as the patterns being suggested and used by the user then the software pushes all the suggested pattern elements in the solution matrix index. In addition, this algorithm will also remove the duplicates about parts or machines in the tables as the transit to this node by the other parts or machines is voided. This is more effective than all other methods in transiting the graph more efficiently.

Merge Pattern: The merge pattern is partial implementation of similar pattern, unlike the condition is changed. If there exist sequences about which initial and final node of those sequences is repeated, then the tool identifies as the merge pattern and does not take account of middle nodes. This is due to most of the intermediate nodes being either cancelled or taken by another pattern in the preceding index, hence to increase chances of the coverage of the element this pattern can be applied. This method helps mostly in highly randomised and reductant matrix.

Longest Path Last Node reference: this is an exotic algorithm and rarely used. This algorithm is suited best for the sparse matrix and helps in preserving the order of cancellation. For the given longest path, the last node of it will refer to the next sequence start node, and this may lead to chain selection suggestion.

The best choice of the above algorithm or the combination of above algorithms is solely depending on the user who is interacting with the interface. Moreover, the tool suggests the possible detected patterns and by following the suggestion the user may get the optimal solution. However, it is guaranteed that any given CMS grouping problem will have at least two or more possible patterns into the matrix.

2.1 PROCEDURE FOR APPLYING IBC TO CF PROBLEMS

The sample solution for solving a random benchmark problem is discussed next, which helps in the understanding the tool and the contextual solution guide. Consider the following 10X10 sized Machine Component matrix (Table 1) as described by (Mosier and Taube (1985a).

Table 1: The input Matrix for the solution instance

		Parts									
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Machines	**1**	1	0	0	1	0	1	0	0	0	0
	2	0	0	0	0	0	0	0	0	1	1
	3	0	1	0	0	0	0	1	0	1	1
	4	0	1	0	0	0	0	0	0	1	1
	5	0	0	1	0	0	0	0	0	0	0
	6	0	0	1	0	0	0	0	1	0	0
	7	0	0	0	0	1	1	0	0	0	0
	8	0	1	0	0	0	0	1	0	1	0
	9	0	0	0	0	0	0	0	1	0	0
	10	1	0	0	0	1	1	0	0	0	0

Table 2: The Part I/O table generated from pattern search.

Machine no	Part node						
	In node	Intermediate node		Out node	LGP	SP	MG
1	1			10			MG
2	3	4		8			MG
3	5			6			
4	1			1			
5	7			10			
6	1	7		10			MG
7	3			8			MG
8	6			9			
9	2	3	4	8	LGP		
10	2	3		4			

Here after the input matrix is built in the software the I/O tables (Tables 2 and 3) are generated based upon the mutual referencing as discussed in the section above.

From the Table 2 it is found that the machine is transiting through the various part nodes and there are two different patterns that emerged where machine 9 is transiting through the maximum number of the nodes.

Table 3: The Machine I/O table generated from pattern search.

Part no	Machine node						
	In node	Intermediate node		Out node	LGP	SP	MG
1	1	4		6			MG
2	9			10			
3	2	7	9	10	LGP		MG
4	2	9		10			MG
5	3			3			
6	3			8			
7	5			6			
8	2	7		9			
9	8			8			
10	1	5		6			MG

The solution achieved is presented in Figure 5. The above problem had only two detected patterns and thus it is very easy for the user to iterate over the selection of the suggestion given by the tool.

	2	7	9	10	1	4	6	5	3	8
2	0	0	1	1	0	0	0	0	0	0
3	1	1	1	1	0	0	0	0	0	0
4	1	0	1	1	0	0	0	0	0	0
8	1	1	1	0	0	0	0	0	0	0
1	0	0	0	0	1	1	1	0	0	0
10	0	0	0	0	1	0	1	1	0	0
7	0	0	0	0	0	0	1	1	0	0
5	0	0	0	0	0	0	0	0	1	0
6	0	0	0	0	0	0	0	0	1	1
9	0	0	0	0	0	0	0	0	0	1

Figure 5: The final solution achieved by selecting the suggestion of pattern indexes given by the IBC

From the above example solution, the number of the suggested patterns from the input matrix were 2 and the decision of choosing the best suggest pattern is very easy. However, in some instances, the number of suggest patterns could encompass all patterns, then user must follow the guidelines described in the above section or implement trial and error method to explore the solution. One such implementation example was discussed as follows. The following matrix is a good example which showcases the ability of the proposed collection of algorithms that can handle sparse matrix and produced optimised result than GRASP heuristics.

Table 4: The input Matrix for the solution instance

		Parts													
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
Machines	**1**	0	0	0	1	1	0	1	0	0	0	0	0	0	0
	2	0	0	0	1	1	0	1	0	0	0	0	0	0	0
	3	0	1	1	0	0	0	0	0	0	1	1	0	0	0
	4	0	1	0	0	0	0	0	0	0	0	1	0	0	0
	5	0	0	0	0	0	0	0	1	1	0	0	0	0	0
	6	1	0	0	0	0	0	0	0	0	0	0	0	1	0
	7	0	0	0	0	0	0	1	0	0	0	0	1	1	0
	8	1	0	0	0	0	0	0	0	0	0	0	1	0	0
	9	0	0	0	0	0	0	0	0	1	1	0	0	0	1
	10	0	0	0	0	0	1	0	1	0	0	0	0	0	0
	11	0	0	0	0	0	1	0	1	0	0	0	0	0	0
	12	0	0	0	0	0	1	0	1	1	0	0	0	0	0
	13	0	0	0	0	0	0	0	0	1	0	0	0	0	0
	14	0	0	0	0	0	1	0	1	0	0	0	0	0	0
	15	0	0	0	0	0	1	0	1	1	0	0	0	0	0
	16	0	0	0	0	0	1	0	1	0	0	0	0	0	0
	17	0	0	0	1	1	0	1	0	0	0	0	0	0	0
	18	0	0	0	1	1	0	0	0	0	0	0	0	0	0
	19	1	0	0	1	1	0	1	0	0	0	0	0	0	0
	20	0	0	0	1	1	0	1	0	0	0	0	0	0	0
	21	0	0	1	0	0	0	0	0	0	0	1	0	0	0
	22	0	0	0	0	0	1	0	1	0	0	0	0	0	0
	23	0	0	0	1	1	0	0	0	0	0	0	0	1	0
	24	0	0	0	0	0	0	0	0	0	1	1	0	0	0

The generated I/O tables for the above matrix were given as follows, these tables have three suggested patterns. the various solution instances were given with respective to the different pattern sequences.

Table 5: The Part I/O table generated from pattern search.

Machine no	Part node										
	In node	Intermediate node						Out node	LGP	SP	MG
1	6	7	8	18				19			
2	3	3		4				4			
3	3	3	4					21			
4	1	2	17	19	20			23		SP	MG
5	1	2	17	19	20			23		SP	MG
6	9	10	11	12	14	15	16	22	LGP		
7	1	2	7	17	19			20			
8	5	10	12	14	15	16		22			
9	5	9	12	13		4		15			
10	3	9						24			MG
11	3	4	21					24			MG

12	7							8			
13	6	7						23			
14	9	11	13					15			

Table 6: The Machine I/O table generated from pattern search.

Part no	Machine Node						
	In node	Intermediate node		Out node	LGP	SP	MG
1	4	5		7		SP	MG
2	4	5		7		SP	MG
3	2	3	10	11	LGP		MG
4	2	3		11			MG
5	8			9			
6	1			13			
7	1	7	12	13	LGP		MG
8	1			12			
9	6	9	10	14	LGP		MG
10	6			8			
11	6			14			
12	6	8		9			
13	9			14			
14	6			8		SP	MG
15	6	8	9	14	LGP		MG
16	6			8		SP	MG
17	4	5		7		SP	MG
18	1			1			
19	1	4	5	7	LGP		
20	4	5		7		SP	MG
21	3			11			
22	6			8		SP	MG
23	4	5		13			
24	10			11			

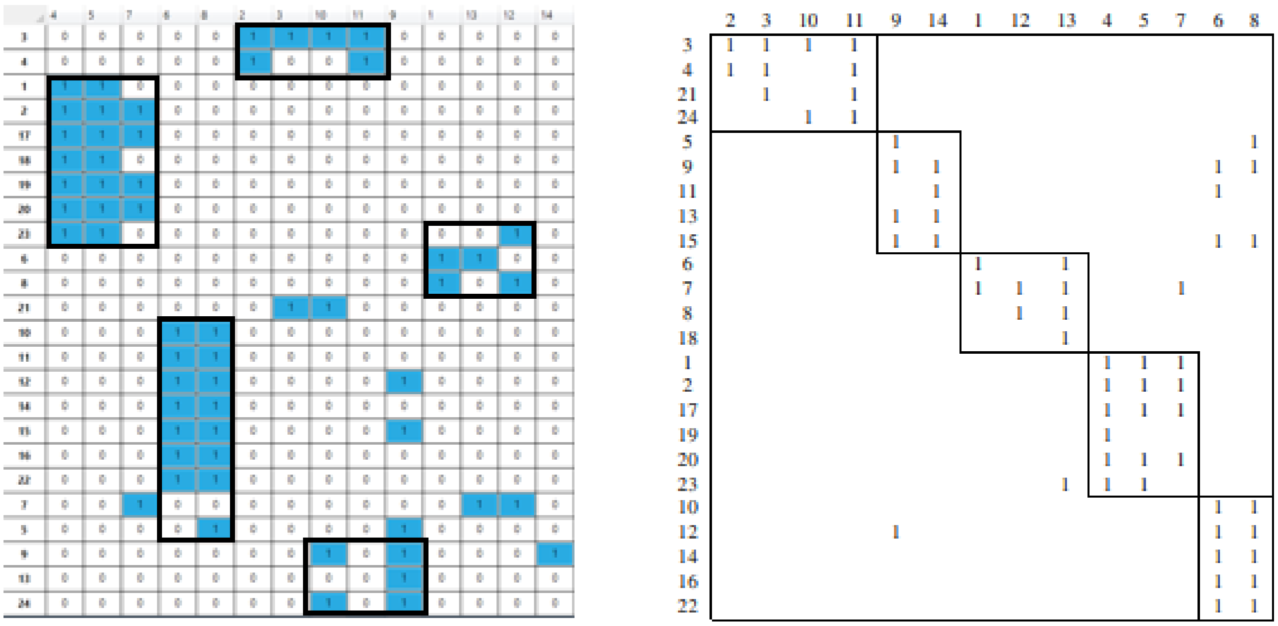

Figure 6: The generated Machine and Part I/O tables for the 24 X 14 sized input Matrix, (a) solution matrix generated by the IBC and (b) solution matrix generated by the GRAPS heuristics.

It can be noted from the above solution, the number of exceptions are equal and moreover the IBC had grouped the cell with fewer exceptions when compared to GRAPS heuristics. This proves the efficiency of the using IBC in forming clusters in the CF problems. Therefore, by implementing the suggested pattern by the IBC, more alternatives can be verified and explored for optimising the solution.

3. RESULTS

For the given methodology, the benchmarking is done based on the five parameters Grouping efficacy, Machine utilisation, Cell efficiency, Grouping efficiency and Wall time over the selected 10 problems of various matrix sizes (Table 4). However, the wall time of current approach is high compared to the benchmark method GRASP. But the results show that the wall time for the given IBC is under 1s for all the cases tested., the Following table gives some results as a comparison over various methods.

Table 7: The performance parameters is given in following dataset.

PERFORMANCE PARAMETERS	Problem	GRASP	ROC[1]	IBC
Grouping efficacy	(King & Nakornchai, et al., 1982)	0.736842	0.736842	0.736842
Machine utilisation		0.823	0.823	0.823
Cell efficiency		0.755	0.755	0.755
Grouping efficiency		0.800	0.800	0.800
Grouping efficacy	(A.Kusiak, et al., 1992)	0.769	0.769	0.769
Machine utilisation		0.833	0.833	0.833
Cell efficiency		0.7878	0.7878	0.7878

[1] ROC-Rank Order Clustering

Grouping efficiency		0.833	0.833	0.833
Grouping efficacy	(Boctor, et al., 1991)	0.703	0.703	0.703
Machine utilisation		0.760	0.760	0.760
Cell efficiency		0.817	0.817	0.817
Grouping efficiency		0.841	0.841	0.841
Grouping efficacy	(H. Seifoddini et al., et al., 1986)	0.682	0.651	0.682
Machine utilisation		0.823	0.777	0.823
Cell efficiency		0.728	0.707	0.728
Grouping efficiency		0.798	0.772	0.798
Grouping efficacy	(Mosier.Charles, et al., 1985)	0.705	0.705	0.705
Machine utilisation		0.705	0.705	0.705
Cell efficiency		0.883	0.883	0.883
Grouping efficiency		0.852	0.852	0.852
Grouping efficacy	(Chan & Milner, et al., 1982)	0.920	0.920	0.920
Machine utilisation		0.920	0.920	0.920
Cell efficiency		0.962	0.962	0.962
Grouping efficiency		0.960	0.960	0.960
Grouping efficacy	(Stanfel, et al., 1985)	0.603	0.62	0.62
Machine utilisation		0.826	0.834	0.834
Cell efficiency		0.643	0.66	0.66
Grouping efficiency		0.7678	0.776	0.776
Grouping efficacy	(Carrie, et al., 1973)	0.540	0.540	0.540
Machine utilisation		0.705	0.705	0.705
Cell efficiency		0.644	0.644	0.644
Grouping efficiency		0.775	0.775	0.775
Grouping efficacy	(Chandrasekharan & Rajagopalan, et al., 1986)	1.0	1.0	1.0
Machine utilisation		1.0	1.0	1.0
Cell efficiency		1.0	1.0	1.0
Grouping efficiency		1.0	1.0	1.0

On comparison between various methods, the new method (IBC) had performed in line with the nearest benchmarking Algorithm (GRASP) without any advanced algorithms, but just with natural pattern recognition.

As it can be seen from Figure 6, the wall time of the IBC for all the problems are aligned and were mostly near equal to the range of the GRASP (Díaz et al., 2012) algorithm. In few cases the algorithm had outperformed GRASP.

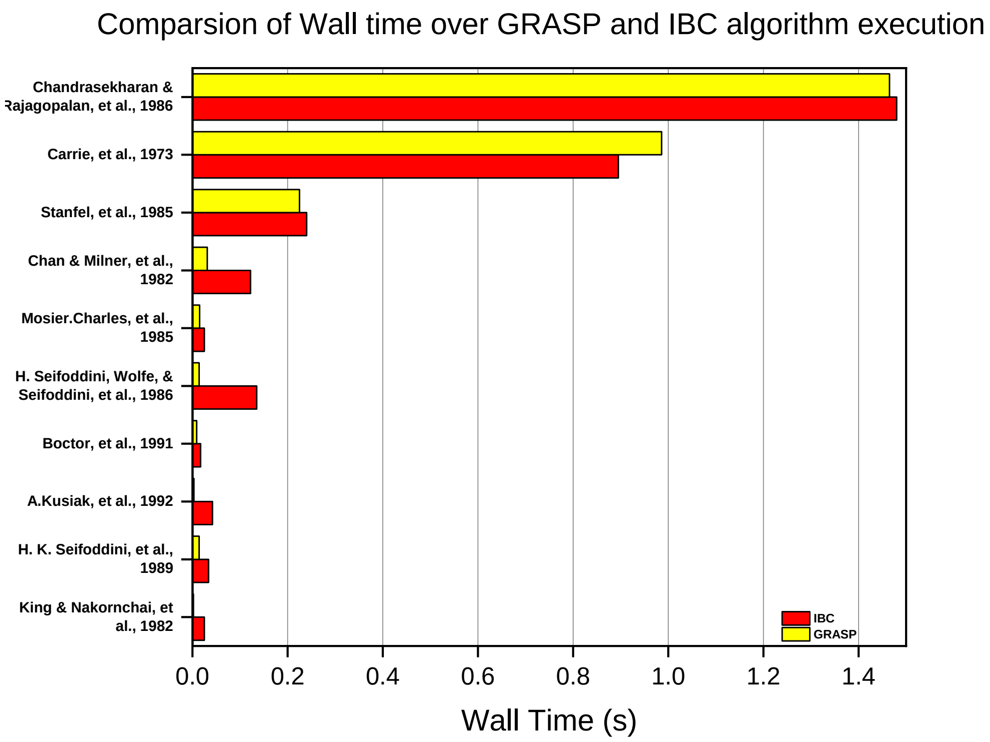

Figure 7: The wall time comparison of GRASP and IBC

From the above figure, it can be observed that as the matrix size is increasing the wall time (time taken to compute the solution) is also increased and the on careful observation, the wall time for IBC is greater than GRASP method. However, the solution provided by the IBC were more optimised with fewer exceptions in the cell as shown in figure 6 in section 2.1. For most of the small scale problems, only visual depiction is need to process CF problems by implementing the IBC manually.

4. CONCLUSION

In this paper an Inspection Based Clustering (IBC) approach, has been put forward to enable to support solving manufacturing cell formation problems properly and easily with no need for further complex mathematical modelling. The approach is based on human cognition inspired procedure having revealed to be a successful implementation of a partial artificial intelligence module (based on pattern recognition), which has been used as a novel contribution to prove the cellular formation or more concretely binary related problems that can be solved using the proposed IBC based approach. The comparison of the benchmark problems used are discussed in this paper regarding a set of performance measures for cellular manufacturing systems (CMS) studies, based on family parts formation procedures evaluation: grouping efficacy, machine utilisation, cell efficiency, and grouping efficiency, along with the wall time evaluation. The main drawback of GRASP method is it cannot be implemented manually and there is no readymade tool to approach the problem. Moreover, the algorithm does not minimize the expectations in the cell. On contrast, the outcomes of the GRASP are quick. The Rank Order Clustering (ROC) is a legacy method and is proven to work manually and using a computer and the time taken to obtain the solution is dependent on the size of the matrix. The main advantage of the IBC is that there is no mathematical quantification rather than searching for pure patterns in the Matrix and this method can be approached manually without any formal training in CMS [Cellular manufacturing Systems] and it not designed only to address CF but a large class of problems such as forming Teams, designing transportation hubs etc. The main drawback of IBC is that the patterns are callable based on the user request, but can be read sequentially based on the selected patterns by the user.

The proposed IBC approach, along with its internal algorithms have proved to enable to effective and efficiently help in solving large data set based algorithms for CMS in minimum time span when compared with other approaches from the literature. In addition, the developed software is made available in the GitHub link https://github.com/Nagasairam112/IBC and open source, I t is encouraged for all users and readers to try out the proposed IBC approach, which aid in better understand its underlying methodology.

In terms of future work, the application of the proposed IBC based approach for solving other kind of clustering problems, for instance for grouping manufacturing resources or machines in a functional or process oriented manufacturing environment and for forming complex and flexible job shops, and also further to be explored in the context of cyber physical production systems.

Acknowledgements

This work has been supported by national funds through FCT – Fundação para a Ciência e Tecnologia within the [UID/CEC/00319/2019] project and within the RD Units Project Scope: UIDP/04077/2020 and UIDB/04077/2020.

REFERENCES

Abbasi, B., Shadrokh, S., & Arkat, J. (2006). Bi-objective resource-constrained project scheduling with robustness and makespan criteria. Applied mathematics and computation, 180(1), 146-152.

Alves, F., Varela, M. L. R., Rocha, A. M. A., Pereira, A. I., & Leitão, P. (2019). A Human Centred Hybrid MAS and Meta-Heuristics Based System for Simultaneously Supporting Scheduling and Plant Layout Adjustment, *FME Transactions*, 47(4), 699-710. Belgrade University. DOI: 10.5937/fmet1904699A.

Andres, C., & Lozano, S. (2006). A particle swarm optimization algorithm for part–machine grouping. Robotics and Computer-Integrated Manufacturing, 22(5-6), 468-474.

Arkat, J., Saidi, M., & Abbasi, B. (2007). Applying simulated annealing to cellular manufacturing system design. The International Journal of Advanced Manufacturing Technology, 32(5-6), 531-536.

Attila Islier*, A. (2005). Group technology by an ant system algorithm. International Journal of Production Research, 43(5), 913-932.

Bortolini, M., Galizia, F. G., & Mora, C. (2019). Dynamic design and management of reconfigurable manufacturing systems. *Procedia manufacturing*, 33, 67-74.

Dagli, C., & Huggahalli, R. (1995). Machine-part family formation with the adaptive resonance theory paradigm. The International Journal of Production Research, 33(4), 893-913.

Danilovic, M., & Ilic, O. (2019). A novel hybrid algorithm for manufacturing cell formation problem. *Expert Systems with Applications*, 135, 327-350.

Díaz, J. A., Luna, D., & Luna, R. (2012). A GRASP heuristic for the manufacturing cell formation problem. TOP, 20(3), 679-706. doi:10.1007/s11750-010-0159-3

Dorigo, M., Caro, G. D., & Gambardella, L. M. (1999). Ant algorithms for discrete optimization. Artificial life, 5(2), 137-172.

Durán, O., Rodriguez, N., & Consalter, L. A. (2008). A PSO-based clustering algorithm for manufacturing cell design. in the Proceedings of the 1st international conference on Forensic applications and techniques in telecommunications, information, and multimedia and workshop.

Eliguzel, I. M., & Ozceylan, E. (2019). Comparison of Different Clustering Methods for Cellular Manufacturing: A Case of Gym Centre. *Procedia Computer Science*, 158, 1-8.

Elmaraghy, H., & Gu, P. (1989). Feature based expert parts assignment in cellular manufacturing. Journal of Manufacturing systems, 8(2), 139-152.

Joines, J. A., Culbreth, C. T., & King, R. E. (1996). Manufacturing cell design: an integer programming model employing genetic algorithms. IIE transactions, 28(1), 69-85.

Laha, D., & Hazarika, M. (2017). A heuristic approach based on Euclidean distance matrix for the machine-part cell formation problem. *Materials Today: Proceedings*, 4(2), 1442-1451.

Liang, M., & Zolfaghari, S. (1999). Machine cell formation considering processing times and machine capacities: an ortho-synapse Hopfield neural network approach. Journal of Intelligent Manufacturing, 10(5), 437-447.

Lozano, S., Canca, D., Guerrero, F., & Garcıa, J. (2001). Machine grouping using sequence-based similarity coefficients and neural networks. Robotics and Computer-Integrated Manufacturing, 17(5), 399-404.

Metropolis, N., Rosenbluth, A. W., Rosenbluth, M. N., Teller, A. H., & Teller, E. (1953). Equation of state calculations by fast computing machines. The journal of chemical physics, 21(6), 1087-1092.

Nalluri, M. S. R., Kannan, K., Gao, X. Z., & Roy, D. S. (2019). An efficient hybrid meta-heuristic approach for cell formation problem. *Soft Computing*, 23(19), 9189-9213.

Neto, A. R. P., & Gonçalves Filho, E. V. (2010). A simulation-based evolutionary multiobjective approach to manufacturing cell formation. Computers & Industrial Engineering, 59(1), 64-74.

Onwubolu, G. C., & Mutingi, M. (2001). A genetic algorithm approach to cellular manufacturing systems. Computers & Industrial Engineering, 39(1-2), 125-144.

Ostrosi, E., & Fougères, A. J. (2018). Intelligent virtual manufacturing cell formation in cloud-based design and manufacturing. *Engineering Applications of Artificial Intelligence*, 76, 80-95.

Pan, C., Zhou, M., Qiao, Y., & Wu, N. (2017). Scheduling cluster tools in semiconductor manufacturing: Recent advances and challenges. *IEEE transactions on automation science and engineering*, 15(2), 586-601.

Papaioannou, G., & Wilson, J. M. (2010). The evolution of cell formation problem methodologies based on recent studies (1997–2008): Review and directions for future research. European journal of operational research, 206(3), 509-521.

Prabhaharan, G., Asokan, P., Girish, B., & Muruganandam, A. (2005). Machine cell formation for cellular manufacturing systems using an ant colony system approach. The International Journal of Advanced Manufacturing Technology, 25(9-10), 1013-1019.

Prasad, D., & Jayswal, S. C. (2019). Assessment of a reconfigurable manufacturing system. *Benchmarking: An International Journal*.

Rajesh, P., Gupta, N. S., & Rajendran, C. (2020). Investigations on the input processing schema for the machine-part cell formation using CARI Heuristic. *Materials Today: Proceedings*, 22, 3312-3319.

Rao, H., & Gu, P. (1995). A multi-constraint neural network for the pragmatic design of cellular manufacturing systems. The International Journal of Production Research, 33(4), 1049-1070.

Renzi, C., Leali, F., Cavazzuti, M., & Andrisano, A. O. (2014). A review on artificial intelligence applications to the optimal design of dedicated and reconfigurable manufacturing systems. The International Journal of Advanced Manufacturing Technology, 72(1), 403-418. doi:10.1007/s00170-014-5674-1

Rezaeian, J., Javadian, N., Tavakkoli-Moghaddam, R., & Jolai, F. (2011). A hybrid approach based on the genetic algorithm and neural network to design an incremental cellular manufacturing system. Applied Soft Computing, 11(6), 4195-4202. doi:https://doi.org/10.1016/j.asoc.2011.03.013

Sayadi, M. K., Hafezalkotob, A., & Naini, S. G. J. (2013). Firefly-inspired algorithm for discrete optimization problems: An application to manufacturing cell formation. Journal of Manufacturing systems, 32(1), 78-84. doi:https://doi.org/10.1016/j.jmsy.2012.06.004

Selim, H. M., Askin, R. G., & Vakharia, A. J. (1998). Cell formation in group technology: Review, evaluation and directions for future research. Computers & Industrial Engineering, 34(1), 3-20. doi:https://doi.org/10.1016/S0360-8352(97)00147-2

Singh, S., & Singhal, S. (2020). Implementation and analysis of the clustering process in the enhancement of manufacturing productivity. *Journal of King Saud University-Engineering Sciences*.

Solimanpur, M., Vrat, P., & Shankar, R. (2004). A multi-objective genetic algorithm approach to the design of cellular manufacturing systems. International Journal of Production Research, 42(7), 1419-1441.

Sridhar, J., & Rajendran, C. (1993). Scheduling in a cellular manufacturing system: a simulated annealing approach. The International Journal of Production Research, 31(12), 2927-2945.

Subramaniyan, M., Skoogh, A., Muhammad, A. S., Bokrantz, J., Johansson, B., & Roser, C. (2020). A generic hierarchical clustering approach for detecting bottlenecks in manufacturing. *Journal of Manufacturing Systems*, 55, 143-158.

Sudhakara Pandian, R., & Mahapatra, S. S. (2009). Manufacturing cell formation with production data using neural networks. Computers & Industrial Engineering, 56(4), 1340-1347. doi:https://doi.org/10.1016/j.cie.2008.08.003

Vakharia, A. J., & Chang, Y. L. (1990). A simulated annealing approach to scheduling a manufacturing cell. Naval Research Logistics (NRL), 37(4), 559-577.

Varela, M. L. R.; Ribeiro, R. A. (2003). Evaluation of Simulated Annealing to solve fuzzy optimization problems, Journal of Intelligent and Fuzzy Systems, 14(2), 59-71, IOS Press.

Varela, M. L. R., Manupati, V. K., Manoj, K., Putnik, G. D., Araújo, A., & Madureira, A. M. (2016, December). Industrial plant layout analyzing based on SNA. In International Conference on Intelligent Systems Design and Applications, Advances in Intelligent Systems and Computing (pp. 728-737). Springer. DOI: 10.1007/978-3-319-53480-0_72

Varela, M.L.R., Manupati, V.K., Panigrahi, S., Costa, E. and Putnik, G.D. (2020). Using social network analysis for industrial plant layout analysis in the context of industry 4.0, *International Journal of Industrial and Systems Engineering*, 34(1), 1–19. https://pure.solent.ac.uk/en/publications/using-social-network-analysis-for-industrial-plant-layout-analysi

Venkumar, P., & Haq, A. (2006). Complete and fractional cell formation using Kohonen self-organizing map networks in a cellular manufacturing system. International Journal of Production Research, 44(20), 4257-4271.

Venkumar, P., & Haq, A. N. (2005). Manufacturing cell formation using modified ART1 networks. The International Journal of Advanced Manufacturing Technology, 26(7-8), 909-916.

Venugopal, V., & Narendran, T. (1992a). Cell formation in manufacturing systems through simulated annealing: an experimental evaluation. European journal of operational research, 63(3), 409-422.

Venugopal, V., & Narendran, T. (1992b). A genetic algorithm approach to the machine-component grouping problem with multiple objectives. Computers & Industrial Engineering, 22(4), 469-480.

Wu, T.-H., Chang, C.-C., & Chung, S.-H. (2008). A simulated annealing algorithm for manufacturing cell formation problems. Expert Systems with Applications, 34(3), 1609-1617.

Xambre, A. R., & Vilarinho, P. M. (2003). A simulated annealing approach for manufacturing cell formation with multiple identical machines. European journal of operational research, 151(2), 434-446.

Yang, M.-S., & Yang, J.-H. (2008). Machine-part cell formation in group technology using a modified ART1 method. European journal of operational research, 188(1), 140-152.

Zolfagha Ri, S., & Liang, M. (1997). An objective-guided ortho-synapse Hopfield network approach to machine grouping problems. International Journal of Production Research, 35(10), 2773-2792.

Zupan, H., Herakovic, N., Zerovnik, J., & Berlec, T. (2017). Layout optimization of a production cell*. International Journal of Simulation Modelling*, 16(4), 603-616.