A review on the multi-objective cell formation problem in cellular manufacturing systems

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Abstract: With the advent of cellular manufacturing systems and consequent evolution of configuring methodologies, researchers proposed several multi-objective techniques, besides others, to handle different types of cell formation problems. This paper presents a systematic review on types of cell formation by using multi-objective techniques. It also delineates the type of objectives, production factors and datasets used for testing the efficacy of methodologies, considered by researchers along with the scope and direction of future studies.

Keywords: cellular manufacturing system; CMS; cell formation; multi-objective programming; weighted aggregate method; Pareto optimality; soft computing.

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1 Introduction

In production industries, cellular manufacturing system (CMS) has been identified as an efficient technique to organise the machine and parts to harness advantages of both; mass production and flexibility. The design of CMS is primarily based on identification of parts to be processed in selected group of machines. The machines are grouped according to the processing sequence or characteristics of the parts. The group of parts is then allocated to appropriately identified groups of machines to get the advantages of group technology (GT) (Burbidge, 1975). The concept of GT (Burbidge, 1975) was introduced to identify the similar parts either by shape and size or by processing sequence, which in turn helps to classify the parts. The group of machines are called cells and issues involved in the machine-part grouping are referred to as cell formation problem (CFP). Usually, CFP is useful to handle a wide variety of parts having similar processing or feature characteristics. The CFP helps to design the manufacturing systems by grouping the similar parts into part families and their associated machines into cells. Ideally, each part family should be processed in a single cell. The primary goal of CFP is to group machines into clusters by satisfying certain production factors. The common production factors are minimisation of inter cellular movements of parts, cell load variation, make span, exceptional elements, number of voids, etc. The purpose of cell formation is to reduce the total production cost by satisfying those factors as objective.

Several techniques, like classification and coding systems, cluster analysis, graph partitioning theory, mathematical programming methods as well as heuristics, meta-heuristics and artificial intelligence (Arora et al., 2013) are used to solve the CFP. The majority of the techniques deal with problems considering only one objective function (Shankar and Vrat, 1999) to avoid the complexity and computational hardness. Unfortunately, CFPs are inherently multi-objective in nature. Therefore, these single-objective techniques are, in general, not suitable for solving CFP. So, multi-objective approaches get more importance to solve CFPs.

This study focuses on providing an extensive review on multi-objective cell formation (MOCF) problems. We first identify two major types of cell formation considered by various researchers. They are predefined cell number and dynamic cell formation (DCF). Secondly, the classifications of the methods used for solving MOCFP are done under two broad categories – the weighted sum and Pareto-optimal approaches. Furthermore, we identify major objectives, production parameters and type of test datasets to identify the superiority of the proposed approaches. An analysis is done to compare the results of different methods for different cell formation categories to identify the recent research trends in the field of CMS. Future research areas along with unexplored areas for both types of cell formations are also delineated.

The remainder of the paper is organised as follows: following the introduction, Section 2 presents an overview on cell formation and its types. Section 3 shows the general form of MOCFP and Section 4 illustrates a brief discussion on different approaches to solve different types of MOCFP. Results and analysis, based on aforesaid review is discussed in Section 5 and the future scope of research and conclusions are presented in Sections 6 and 7, respectively.

2 Types of cell formation

Researchers have proposed different types of cell formation techniques based on the requirement of manufacturing systems. Initially, different models proposed to solve CFP by considering a fixed number of cells (predefined number of cells). With the evolution of new techniques, cells are formed dynamically, which is termed as DCF.

2.1 Predefined number of cells

Cell formation in manufacturing systems started with the fixed number of cells specified by the decision maker. Generally, large problems need more number of cells than smaller problems. This process is beneficial for usual production systems, where product variation is less and floor space is limited. With fixed number of cells, fixed cost and labour allocations can be effected antecedently which helps in estimating the overall production cost.

2.2 Dynamic cell formation

Modern manufacturing industries deal with product variation, demand variation and uncertainty in labour allocation, etc. In such situations, it is not always possible to allocate machines in a pre-defined number of cells to obtain the best group performance. To overcome these limitations, DCF is adopted as a better alternative in CMS. In DCF, machines are grouped dynamically in cells so that the generated cells are independent to each other with maximum compactness.

3 The general form of a MOCF problem

A MOCFP can be represented as follows (Zitzler and Thiele, 1999):

$$\min : y = \left(f_1(x), f_2(x), \ldots, f_m(x)\right)$$

subject to

$$x = \left(x_1, x_2, \ldots, x_n\right) \in X$$

$$y = \left(y_1, y_2, \ldots, y_m\right) \in Y$$

where x is an n-dimensional decision vector, X is the parameter space, y is an m-dimensional objective vector and Y is the objective space. The objective vector y may include objectives such as inter cellular movements, cell load variation, machine investment, machine relocation cost, setup cost, exceptional elements, machine utilisation, level of work-in-progress, machine duplication, system utilisation, part processing, part routing, defective part replacement.

Various techniques have been proposed in the literature to solve MOCF problems for both pre-defined cell number and DCF. They are classified as weighted sum approach (Gupta et al., 1996) and Pareto-optimal approach (Branke et al., 2008).

3.1 Weighted sum approach

It is one of the most popular approaches to solve MOCFP in which the weights are assigned to individual objectives according to their priority. The major drawback of these approaches is the sensitivity towards the weights or priority variations. The decision makers must have a prior knowledge of individual objectives before summing them up. Different weighting factors may also be used to solve the problem under different situations.

3.2 Pareto-optimal approach

To overcome the limitations of the weighted sum approaches, Pareto-optimal approaches have been proposed. A set of non-dominated solutions are identified within the solution space considering all objectives. A fitness sharing technique is developed to solve the problems by avoiding the convergence of the algorithm of non-dominated solutions. Based on the concept of ranking and fitness sharing, this approach guides to develop several techniques such as, non-dominated sorting genetic algorithm (NSGA) (Srinivas and Deb, 1994), niche Pareto genetic algorithm (NPGA) (Horn et al., 1993), strength Pareto evolutionary algorithm (SPEA) (Zitzler and Thiele, 1999) that offer an improved performance over the traditional multi-objective algorithms.

4 Discussions

In this section, we discuss weighted sum and Pareto-optimal approaches used for solving CFPs separately.

4.1 Weighted sum approaches for predefined cell number

In weighted sum approaches, several methods are proposed depending on different underlying methodologies and objectives. These approaches are classified and discussed next.

4.1.1 Multi-objective cluster analysis

In their work, Akturk and Balkose (1996) considered a MOCFP with objectives – minimising dissimilarity of parts based on design, manufacturing characteristics, operation sequence, total machine investment cost, minimising cell load variation and exceptional elements. They performed the multi-objective cluster analysis to normalise objectives in different units and finally used the weighted sum approach to find the cell layout design.

4.1.2 Fuzzy-based approach

Arikan and Gungor (2009) developed a fuzzy-based technique to solve the MOCFP. The problem has three objectives – maximisation of machine utilisation capacity, minimisation of cost related to exceptional elements and number of inter-cell operations that are defined fuzzily to incorporate the uncertainty of the decision-making environment. Nunkaew and Phruksaphanrat (2013) proposed a lexicographic fuzzy multi-program model to handle the duplicate machines. They considered minimisation of exceptional elements and number of voids as objectives and find their relationship with duplicated machines. They used literature dataset to test their model. With the same objectives, they developed another model to capture the flexibility of proposed fuzzy-multi-objective model by using an integer programming solvers.

4.1.3 Genetic algorithm approach

Gupta et al. (1996) initiated the use of genetic algorithm (GA) to solve CF problems. They developed a model considering minimisation of total parts movement and workload variation in the cell and considered different weighting structure for inter and intra cell movements. They adopted two distinct populations to estimate the objective functions separately and tried to find out similarity of chromosomes. To minimise total costs including parts movement within and between the cells, machine investment cost and cell load variation, Hsu and Su (1998) proposed a GA and obtained the impact of the layout of manufacturing cells. Three objectives with different scales and units are normalised and combined to a single objective using the weighted sum approach. They compared the performance of their technique with some other works. Moon and Gen (1999) developed a GA-based integer programming approach considering several production parameters, such as, the production volume, machine capacity, processing time, cell size, alternative process plans and machine duplication, etc. They considered the final objective function as the sum of minimisation of machining and duplication cost. They showed that LINDO program is not suitable for solving problems with large number of constraints and variables. Their approach generated a better result in terms of computation time and problem size.

Considering three objectives – minimisation of cost due to inter and intra cell part movements, total cell load variation and exceptional elements, Zhao and Wu (2000) proposed a GA-based algorithm. They considered alternative routing as production parameter and obtained a compromised solution. The algorithm was applied on a group of machines and improved results were reported by considering large number of parts processing using literature dataset. Onwubolu and Mutingi (2001) proposed a weighted sum approach considering cell load variation and inter cellular movements as objectives. The results, as obtained, were compared with a travelling salesman problem (TSP)-based algorithm and ZODIAC (Chandrasekharan and Rajagopalan, 1986) using literature dataset, and its effectiveness was proved in terms of time and efficiency.

Khoo et al. (2003) proposed an improved model in which the considered objectives are minimisation of gross part movements, cell load variation and machine set-up cost. The first approach was applied to a small size problem and desired solution was obtained. The second and third approaches were applied to solve more complex problems, which provided sub-optimal solutions. They used literature dataset to compare their model. Filho and Tiberti (2006) developed a method based on group encoding to obtain a better layout design. They considered intercellular flow and cell load variation as objectives and used with a special factor (Sfactor) to solve the problem. This proposed factor was the ratio of the two individual objectives. They showed that the number of parts has no effect on the size of solution space. Wu et al. (2006) proposed a hierarchical genetic algorithm (HGA) to solve CF and group layout (GL) problems together. This model consists of factors like operation sequence, demand of parts, machine capacity, transfer batch, etc. To minimise the total part movements including backtracking of inter cell movements and to minimise the exceptional elements, they formulated an integral model that provided an improvement between 2%–20% in terms of group efficacy using literature dataset. They proposed a group mutation technique to speed up the process. However, the method failed for large size problems.

Mahapatra and Pandian (2008) proposed a GA by considering minimisation of cell load variation and exceptional elements as objective and compared their results with K-means and C-linkage clustering algorithms using literature dataset by considering modified grouping efficiency. Chan et al. (2006) developed a two-phase approach to find both CF and GL and tested on literature dataset. In the first phase, a model with objectives involving minimising total number of voids, exceptional elements and maximising machine utilisation was formulated to obtain machine cells and part families. The second phase introduced another mathematical model considering weighted sum of all the objectives to minimise total inter and intracellular part movements. Pillai and Subbarao (2008) proposed a method to handle all the changes in demand and product mixes without any relocation. A dynamic nature of the production environment with fixed machine cell was considered by adopting a multi-period function of product mix and demand. The objectives considered were minimisation of material handling cost and machine acquisition cost. The proposed methodology was useful with a forecast of product mix and variable demand without changing the composition of machines over time and performed better than the adoptive design.

Cao et al. (2008) formulated a mixed integer nonlinear programming model for optimal lot splitting and proposed a GA to solve the CFP. Their considered objectives are to minimise inter-cell movements cost, material handling costs, processing costs, set-up costs as well as defective parts replacement cost and the article reported testing of the model with numerical dataset and showed that it is suitable for solving large size problems.

Bootaki et al. (2014) proposed a technique called GA-AUGMEON, which is the hybridisation of GA and augmented epsilon constraint method. The study considers minimisation of parts movements and maximisation of parts quality. To obtain satisfactory results, the model accommodated worker assignment according to their skills, which is a determining factor for both objectives. The method is tested on some randomly generated examples with small as well as with large size problems. Darla et al. (2014) implemented a model considering minimisation of cell load variation and total parts movements in job shop or batch processing situation and implemented their method on a case problem with predetermined number of cells with a production volume and showed that inter-cell movements can be reduced.

4.1.4 Simulated annealing

Su and Hsu (1998) proposed a parallel-simulated annealing (PSA) algorithm to provide a near-optimal solution for the CF problem. The aim was to minimise the total cost related to parts movement and machine investments and to minimise intra and inter cell machine load unbalance. They normalised and combined them into a weighted objective function by introducing a scalar factor. A comparison of their results with the ones in previous studies are presented along with the analysis proving that the model is adoptive, flexible and efficient adhering to shortest processing time. Baykasoglu et al. (2001) proposed a simulated annealing (SA) algorithm by considering the weighted sum of three objectives – minimisation of parts dissimilarity in a cell, minimisation of cell load variation and minimisation of extra capacity requirements for cell formation. The results obtained from this model are better in comparison to the classical approaches.

Mahesh and Srinivasan (2006) proposed a lexicographic-based SA algorithm to solve an incremental CFP. Minimisation of cycle time for an equivalent part, minimisation of sum of square of unbalanced load of each part on all workstations and minimisation of total work content of the equivalent part were considered as objectives in sequential order with their individual priority. The initial feasible solution considering single objective was compared with the final solution applying SA.

4.1.5 Tabu search

Chang et al. (2013) considered three critical issues in CMS design process. They are cell formation, cell layout and intracellular machine sequence. They considered minimisation of intercellular movements and maximisation of utilisation of machine within a cell, while proposing an effective Tabu search algorithm based on generalised similarity coefficient and introduced a new performance measure devised with consecutive forward flows index to maximise intracellular compactness.

4.2 Pareto-optimal approaches for predefined cell formation

The CMS literature suggests that several authors proposed Pareto-optimal approaches for solving CF problems with predefined cell numbers. In this section, we review these approaches.

4.2.1 Mixed integer nonlinear programming approach

Albadawi et al. (2005) proposed a two-phase method. In the first phase, machines cells were identified through similarity coefficient using factor analysis. In the second phase, parts were arranged in the cells using an integer programming approach. The study considers the number of cells as a dependent variable and tries to overcome the drawbacks of earlier studies. Group efficiency was used to measure the performance of the model and it has been shown that the proposed approach was better compared to other methods.

4.2.2 Genetic algorithm approach

Venugopal and Narendran (1992) proposed a bi-criterion mathematical model. They considered minimisation of cell load variation and the volume of inter-cell movements. The algorithm was tested on generated dataset and the effectiveness of the method was interpreted in terms of computational time while the method is reported to be apposite in complex and large problems. Considering the same objectives, Gravel et al. (1998) proposed a method to generate a set of Pareto-optimal solutions. To avoid the insignificant solutions, the authors maintained the constraints on cell size and on unique assignment of machines to cells as defined by Venugopal and Narendran (1992). Both epsilon-constraint and weighted sum approaches were applied on randomly generated data to obtain an efficient set of solutions. Pierreval and Plaquin (1998) considered same set of objectives and developed an NPGA with a new recombination operator. They first examined a sub-problem comparing a set of individuals to identify the best. The final solution was obtained according to the way the subset of individual was distributed in the search space. The method was tested using industrial data and is shown to be efficient in terms of computational time. Mansouri et al. (2003) developed a multi-objective GA, called as XGA, to obtain a set of non-dominated solutions. Deviation among the cells utilisation has been chosen as the objectives while considering minimisation of intercellular parts movement, total cost for machine duplication and part subcontracting and system underutilisation. The model is compared with the other ones in terms of quality, diversity and CPU time and applied it on dataset retrieved from literature. It was shown that the results were 22.2% better in quality than the others, like VEGA, NPGA and NSGA-II and needed 28.9% less computation time.

Solimanpur et al. (2004) proposed a multi-objective GA to obtain a set of Pareto-optimal solutions involving considerations for the objectives as; maximise the total similarity between parts and minimise the processing cost, processing time and total investment needed for acquisition of machines. This model is more comprehensive and provides better result on problems, using literature dataset, compared to some other studies. Lian et al. (2014) used NSGA-II to form independent manufacturing cells by considering minimisation of cell load variation and inter-cell movements. This technique eliminated the inter-cell movements by allocating identical machines in different cells and was tested on literature dataset to prove its efficiency. Yu et al. (2013) developed a hybrid technique by combining local search into NSGA-II to handle multi-objective decision-making line-cell problem. The treatment considers total throughput time and labour hours as objectives while presenting comparison results.

4.3 Weighted sum approaches for DCF

Like predefined number of cell formation, weighted sum approach was considered by some researcher to solve DCF problems. Methods proposed for solving DCF problems are classified and discussed here.

4.3.1 Multi-objective cluster analysis approach

Goyal et al. (2013) introduced an average linkage hierarchical clustering algorithm to solve reconfigurable manufacturing systems. They considered minimum number of by-passing moves and quantity of idle machines.

4.3.2 Mixed integer nonlinear programming approach

Mehdizadeh et al. (2016) considered cell formation and production planning simultaneously to minimise total costs including machines, parts and workers and minimise the summation of machines idle times as a second objective. They proposed vibration-damping optimisation (MOVDO) for finding Pareto-optimal frontier and compared with NSGAII and NRGA. Small and large-scale datasets were generated to test the model.

4.3.3 Genetic algorithm approach

Brown and Sumichrast (2001) presented the concept of group genetic algorithm (GGA) for solving DCF problems and specified a range of number of cells for allocation of machines within. The attempt has been to minimise the number of voids and exceptional elements in order to maximise group efficiency (Chandrasekharan and Rajagopalan, 1986) and group efficacy (Kumar and Chandrasekharan, 1990) by incorporating weighting factors. They showed that the average improvement was 17% over ZODIAC software using literature dataset. With the same objectives, Yasuda et al. (2005) proposed a GGA by considering parameters like production requirements, machine available time, etc. This method helps to overcome the limitations of cell size constraints. Vin et al. (2005) proposed a multi-objective model to minimise intercellular traffic and to maximise the machine capacity. The study contemplates three production parameters - process sequence, production volume and alternative routing and the proposed model was applied on a case problem to glean the result. Contriving fuzzy part demand and variable product mix, Tavakkoli-Moghaddam et al. (2007) proposed a GA-based fuzzy technique to capture the parts uncertainty and to minimise the machine cost and intercellular movements. Implementation of the technique on literature dataset and evaluation of performance were reported. The authors also proposed reconfiguration of cells to adjust in a dynamic condition. To overcome errors in CFP, Deljoo et al. (2010) developed a model by considering cost minimisation related to machine, operation, intercellular material handling and machine relocation. The result was obtained by summing up all the individual objectives and this approach yielded better result than the one using LINGO. Design of experiments approach for GA was employed by Mohammadi and Forghani (2014) to solve the CFP and cell layout design while contending that it spearheads the accommodation of all design features simultaneously. They considered alternative process routing and subcontracting approaches and used literature dataset to determine efficiency in terms of time and quality, but not without a restriction on the maximum number of fixed cells.

A quasi-DCF was designed by Fan and Feng (2013) by using a nonlinear mixed integer programming model to minimise inter and intra cellular material handling cost, machine relocation cost, worker operation time, loss in batch quality and workers salary. The method was applied to solve the DCF problem to reduce cost and workforce size, as well as to elevate production quality.

Jia and Kong (2013) considered sharable and un-shareable machine to handle four conflicting objectives. The objectives were minimisation of relocation cost, machine utilisation, material handling cost and maintenance cost. Three test problems were considered to ascertain efficiency of the method. A GA-based technique was proposed by Shiyas and Pillai (2014) to minimise the heterogeneity of cells and inter-cell moves. They compared the group efficacy with ZODIAC, GRAFICS, MST, GATSP, GP, EA, HA using literature dataset and showed that the result was reasonably good.

4.3.4 Hybrid GA

Zohrevand et al. (2016) proposed a tabu search-genetic algorithm (TS-GA) to minimise the total cost related to machine, parts and workers and second objective function maximises labour utilisation.

4.4 Pareto-optimal approaches for dynamic CF

Different techniques are proposed to solve CFP with DCF using Pareto-optimal concept. They are summarised below.

4.4.1 Mixed integer nonlinear programming approach

Kia et al. (2013) proposed a model to form dynamic cells and design a cell layout by satisfying two conflicting objectives – minimisation of total cost that includes material handling cost, machine relocation cost, investment, overhead and the cell load variation. The final output produces a set of non-dominated solutions. Comparing the result of individual objectives, it delineates that there was a reverse relationship between these two objectives. This study also claims a better performance in terms of cost and processing time.

4.4.2 Genetic algorithm approach

Dimopoulos (2006) developed a hybrid model, named GP-SLCA, comprising of genetic programming and NSGA-II and contemplated minimisation of total parts movement and cell load variation and tested the method on large-scale problems. The algorithm was executed separately on different constraints while obtaining three different sets of non-dominated solutions that provide better results than Gupta et al. (1996). Neto and Filho (2010) proposed a model by conceiving three objectives, namely, work-in-progress (WIP), intercellular moves and total machinery investment and used a case study problem, retrieved from literature, as well as evaluated its efficiency in terms of performance measure. Arkat et al. (2011) developed two techniques to minimise exceptional elements and number of voids. First, they proposed a ε-constraint model, where one objective was considered and the other was treated as a constraint. This method was not suitable for large-scale problems. In the second method, a Pareto-optimal set of solutions were obtained by using a GA. This technique was applied on literature dataset for large-scale problems within a reasonable time.

Paydar and Saidi-Mehrabad (2013) considered minimisation of voids and exceptional elements to maximise the group efficacy without prior knowledge of number of cells. This study proposes a technique, called GA-VNS (variable neighbourhood search), which has been tested on literature dataset by comparing with ART, graph-neural network, particle swarm optimisation (PSO) and demonstrates its superiority. Izui et al. (2013) implemented a multi-objective GA to solve a robot CMS and tested its efficiency. Bagheri and Bashiri (2014) proposed a genetic imperialist competitive algorithm and verified by same hypothetical numerical examples with different parameters and also tested the model with real world data. Aghajani et al. (2014) used NSGA-II for large-scale and epsilon technique for small size problems, considering minimisation of cost related to machine operating, parts production volume, material handling and subcontracting. The study presents solutions of different randomly generated examples for attesting the efficiency of the technique. A range of cells is specified to optimally allocate the machines. Li et al. (2015) deals with minimisation of total tardiness and total mean flow time to solve sequence dependent flow line manufacturing cell-scheduling problem. A hybrid harmony search (HHS) was developed based on NSGA-II and generated the Pareto front. The technique was compared with NSGA-II, memetic algorithm (MA) and other meta-heuristic technique to prove its efficiency. Niakan et al. (2016) adopted NSGA-II to solve CFP by considering cost minimisation related to machines, parts and workforce and maximising social issues. They used randomly generated datasets to test their model.

4.4.3 Scatter search approach

Bajestani et al. (2009) considered minimisation of cell load variation and sum of other costs, such as, machine cost, inter-cell part movements cost, material handling cost, machine relocation cost. They compared their results with SPEA-II and NSGA-II and indicated the superiority of their approach by using randomly generated data. They built and maintained a uniform set comprised of both diverse and desired solutions.

4.4.4 Simulated annealing approach

Shirazi et al. (2014) applied a SA approach to solve the CF problem and obtained the GL by considering the same objectives as adopted by Kia et al. (2013). The results were compared with the one of NSGA-II and shown to be a satisfactory solution.

4.4.5 Artificial neural network approach

Malakooti and Yang (2002) proposed an artificial neural network (ANN) approach to solve the CF problem involving objectives maximisation of machine utilisation rate and minimisation of the number of exceptional elements. They used an adoptive utility function to find the most preferred alternatives from a set of non-dominated solutions.

4.4.6 Hybrid GA

Alhamdy et al. (2013) developed a hybrid GA-ANN approach consisting of NSGA-II and the weighted similarity coefficient by neural network to generate the Pareto-optimal fronts. Zeidi et al. (2013) used this technique and proved that the model was more efficient than NSGA-II by testing on literature dataset.

4.4.7 Ant colony optimisation

An ant colony optimisation (ACO) technique to solve the CF problem by considering two objectives was used by Rafiei and Ghodsi (2013). The first objective is the sum of machine procurement, relocation cost, intercellular and intracellular movements, overtime cost and labour shifting cost between cells. The second objective is the maximisation of the labour utilisation. An ACO technique and its extended form, hybridisation with GA, were developed to test on randomly generated dataset. It was an early attempt to handle MOCFP using ACO.

5 Results and analysis

The previous section highlights the research on CMS using different multi-objective programming techniques aiming to form specific type of cells. A considerable proportion of research on CMS covers not only the CF problems but also address the design of plant layout dealing with several multi-objective issues. Work in the literature is categorised on the basis of types of CFP and techniques used to solve by considering different objectives. In most of the CF problems, minimisation of the total number of intercellular movements and cell load variation has been considered. Others, like the minimisation of different types of costs and maximisation of machine/cell utilisation, etc. are common objectives considered by different researchers. Large-scale CF problems are sometimes difficult to solve using mathematical programming techniques. As a result, several authors proposed some lower bounds/sub-optimal values to reduce the computational complexity. It is then easier to compare the results with other techniques or with other objectives. The complexity of the problem also increases with the increase in number of machines and cells. In the recent times, Pareto-optimal approaches received more attention and gained popularity for both types of cell formation and it can be attributed to the dynamic nature and complexity of the CFPs. The same are advantageous over the weighted sum approaches. Due to the rapid advancement of the computer technology, many hybrid approaches have also been proposed to solve CFPs. Basically, two different types of hybridisation have been found in the literature. The first one is the component exchange method which works by addition of components of one algorithm to another. The second one is the cooperative search method which indicates a parallel execution of techniques with different level of communication. The other hybridisation is the PSO. This combined the features of GA and SA to overcome the limitations of SA.

Table 1 represents different objectives considered by researchers on CFP. Tables 2a and 2b summarise various techniques and corresponding objectives considered for different types of cell formation.

Table 1 Objectives considered

Objective	*Serial number*
Cell load variation	1
Machine utilisation	2
Part cycle time	3
Total work content for part	4
Extra capacity requirement for machine	5
Part dissimilarity	6
Work-in-progress	7
Part movements	8
Processing time	9
Number of exceptional elements	10
Machine related costs (machine investment, relocation, setup, overhead, operation, new machine, duplication, forming cell, maintenance, material handling, etc.)	11
Part related costs (subcontracting, movements, outsourcing, holding, processing, etc.)	12
Workers related parameters (workers operation time, assignment, etc.)	13
Outer cell operation	14
Number of machine duplication	15
Batch quality loss	16
Number of voids	17
Alternative process routing	18
Quantity of idle machine	19
Total tardiness	20

From Tables 2a and 2b, it is found that about 55% of the studies have been performed on predefined number of cells, whereas about 45% considered DCF. For predefined cell number, weighted sum approach covers more than 73% and Pareto optimal covers only around 27%. In case of DCF, we found an opposite scenario. Weighted sum approaches cover only 40%, whereas, Pareto-optimal approaches cover 60%. Figure 1 shows the percentage of both techniques used for different types of cell formation. GA and GA-based techniques have been considered in about 70% of the published work for both types of cell formation.

It has also been observed that about 59% of the studies consider two objectives, about 27% consider three objectives and rest consider more than three objectives. Some common objectives, like minimisation of cell load variation, intercellular movements and cost related to machines and parts, are considered by a significant number of the studies. Around 45% studies considered the cell load variation, 39% studies considered intercellular movements and about 41% and 33% studies considered cost related to machines and parts, respectively. The other important objectives such as, maximisation of machine utilisation, minimisations of exceptional elements have been considered in about 18% and 16% studies, respectively. It has also been observed that more than 69% of the studies employed GA-based technique under weighted sum and Pareto-optimal approaches. Figure 2 shows the percentage of research articles considering 2, 3 and 4 objectives. Figure 3 shows the percentage of primary objectives considered by different researchers.

Table 2a Techniques used and objectives considered for predefined cell number

Author(s)	*Technique*	*Objectives considered*
Mahesh and Srinivasan (2006)	Lexicographic-based SA	1, 3, 4
Baykasoglu (2001)	SA	1, 5, 6
Akturk and Balkose (1996)	Cluster analysis	1, 6, 11
Albadawi et al. (2005)	Mixed integer programming	2, 6
Moon and Gen (1999)	GA	11, 12
Pillai and Subbarao (2008)	GA	8, 11
Cao et al. (2008).	GA-simplex heuristic	11, 12
Su and Hsu (1998)	PSA	1, 10, 11,12
Arikan and Gungor (2009)	Fuzzy-based approach	2, 11,12, 14
Filho and Tiberti (2006)	GA	1, 8
Khoo et al. (2003)	GA	1, 8, 11
Chan et al. (2006)	GA	2, 8
Hsu and Su (1998)	GA	1, 11,12
Pierreval and Plaquin (1998)	GA-NPEA	1, 8
Solimanpur et al. (2004)	GA-integer programming	6, 9, 11, 12
Venugopal and Narendran (1992)	GA	1, 8
Zhao and Wu (2000)	GA	1, 10, 12
Wu et al. (2006)	GA	10, 12
Gravel et al. (1998)	GA-double loop	1, 8
Mahapatra and Pandian (2008)	GA-heuristic	1, 10
Mansuri et al. (2003)	GA(XGA)	1, 2, 8, 11,12
Onwubolu and Mutingi (2001)	GA	1, 8
Nunkaew and Phruksaphanrat (2013)	Lexicographic fuzzy-based approach	10,17
Nunkaew and Phruksaphanrat (2014)	Fuzzy-based approach	10,17
Chang et al. (2013)	Tabu search	2,8
Lian et al. (2014)	NSGA-II	1,8
Darla et al. (2014)	GA	1,8
Bootaki et al. (2014)	GA-AUGMEON	8,16
Yu et al. (2013)	Local search with NSGA-II	9,13
Gupta et al. (1996)	GA	1,8
Mehdizadeh et al. (2016)	MOVDO	11,12,13,19
Zohrevand et al. (2016)	TS-GA	12, 13, 19

Table 2b Techniques used and objectives considered for DCF

Author(s)	*Technique*	*Objectives Considered*
Kia et al. (2013)	Mixed integer programming	1, 11,12
Shirazi et al. (2014)	SA	1, 11,12
Malakooti and Yang (2002)	ANN	2, 10, 15
Deljoo et al. (2010)	GA	11, 12
Tavakkoli-Moghaddam et al. (2007)	GA-heuristic	11, 12
Fan and Feng (2013)	GA	11,12, 13, 16
Dimopoulos (2006)	NSGA-II	1, 8
Brown and Sumichrast (2001)	GGA	2, 8
Bajestani et al. (2009)	Scatter search (SS)	1, 11,12
Neto and Filho (2010)	GA	7, 8, 11
Yasuda et al. (2005)	GGA	1, 8
Vin et al. (2005)	GGA	1, 2, 8
Arkat et al. (2011)	GA	14,17
Paydar and Saidi-Mehrabad (2013)	GA-VNS	10,17
Rafiei and Ghodsi (2013)	ACO	11,12,13
Goyal et al. (2013)	Cluster analysis	8,19
Shiyas and Pillai (2014)	GA	1,8
Mohammadi and Forghani (2014)	GA	12,18
Li et al. (2015)	HHS based on NSGA-II	9,20
Aghajani et al. (2014)	NSGA-II	11,12
Jia and Kong (2013)	GA	2,11
Niakan et al. (2016)	NSGA-II	11, 12, 13

Figure 1 Percentage of techniques used for both types of cell formation

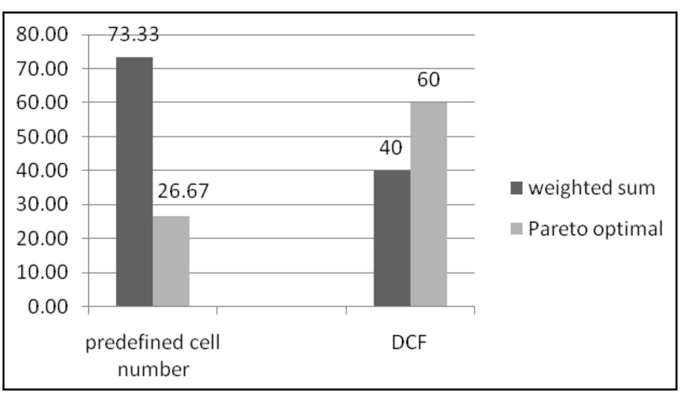


Figure 2 Studies based on number of objectives (see online version for colours)

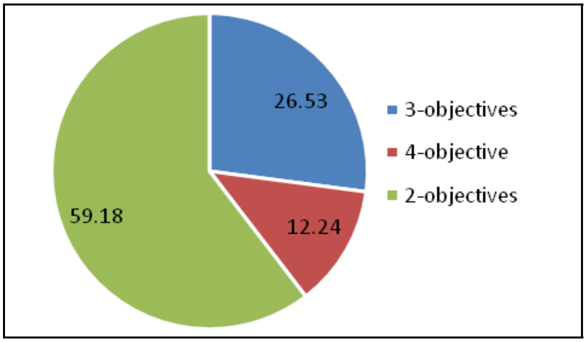
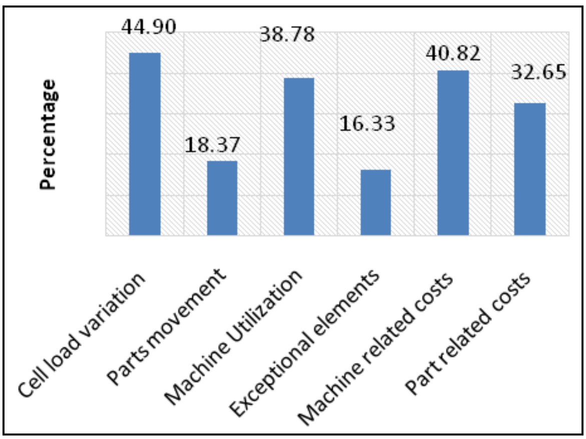


Figure 3 Objectives considered (see online version for colours)



The cost-based objectives related to machines and parts considered by different works are summarised in Table 3.

Cost related to machines comprises of relocation, investment, new purchase, operation, duplication, forming cells, maintenance and material handling. On the other hand, cost related to parts comprises of movements, subcontracting, outsourcing, holding, processing and parts production. From Tables 2a and 2b, it is found that about 41% studies considered cost-based objectives and the same can further be subdivided (Table 3) as related to machine relocation and investment with a proportion of 20% and 17.5%, respectively. Only 10% of each was contributed by machine duplication, overhead and operation. The rest constitutes less than 10%. Around 28% studies considered cost-based objectives related to parts movement. Worker-related costs are considered by negligible portion of the studies.

From the above review, DCF is identified as a recent trend of cell formation for both type multi-objective techniques. Pareto-optimal approaches get more importance over the weighted sum approaches. Hybrid approaches generate better results than the single techniques. Majority of the researchers have tested their methods on literature dataset and remaining few has used real life problems to test their models. Group efficacy becomes more popular as a measure of group performance than group efficiency. Workforce related objectives received more importance in recent time.

Table 3 Cost related objectives based on machines and parts

	Related to machine									*Related to part*						
	Relocation	*Duplication*	*Investment*	*Overhead*	*New machine*	*Forming cells*	*Operation*	*Maintenance*	*Material handling*	*Subcontracting*	*Movements*	*Outsourcing*	*Holding*	*Processing*	*Defective parts*	*Parts production*
Kia et al. (2013)	1	0	0	1	1	1	1	0	0	0	1	0	0	0	0	0
Shiraziet al. (2014)	1	0	0	1	1	1	1	0	0	0	1	1	1	0	0	0
Su and Hsu (1998)	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
Fan and Feng (2013)	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0
Arikan and Gungor (2009)	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0
Bajestani et al. (2009)	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
Khoo et al. (2003)	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Hsu and Su (1998)	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
Solimanpur et al. (2004)	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0
Zhao and Wu (2000)	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Mansouri et al. (2003)	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Deljoo et al. (2010)	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
Moon and Gen (1999)	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Pillai and Subbarao (2008)	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Cao et al. (2008)	0	0	0	0	1	0	0	0	0	1	0	0	0	1	1	0
Tavakkoli-Moghaddam et al. (2007)	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Rafiei and Ghodsi (2013)	1	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0
Jia and Kong (2013)	1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
Aghajani et al. (2014)	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	1
Mehdizadeh et al. (2016)	1	0	1	0	1	0	0	0	0	1	1	0	1	0	0	0
Zohrevand et al. (2016)	1	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0
Niakan et al. (2016)	1	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0

6 Highlighting the future research area

From this study, it is observed that there are some areas that need to be explored more. For example, the performance-based comparisons have been projected in a number of studies, while there is no indication about the objective-based comparisons. Also, less attention has been paid towards cell layout and its related activities, and optimal size of cell for a specific problem. There is a lack of comparison of different cell performance of varying cell size. The involvement of workers, their allocations and ergonomics have not been considered in many studies. Only a few studies consider product variation and its demand, product redesign, variation of parts mix, variation of volume, etc. Flexible (reconfigurable) cell formation design has not been highlighted much which helps to deal with demand and product variation. Similarly, only a few researchers worked with bottleneck machines and there is no specific solution reported for the same. Majority of the work considers only two objectives; cell load variation and total parts movement. However, other production factors, such as, labour utilisation and their allocation; alternative routings received little importance as objective. The benefits of Pareto-optimal solutions showed significant research directions and are discussed only rarely. Most of the researchers have used literature dataset, rather than industrial dataset for the purpose of results comparison.

7 Conclusions

This study presents a review of different types of CFP handled in CMS by using various multi-objective programming techniques. Research articles, explored rather exhaustively in the specific multi-objective domain, are identified and classified based on weighted sum approach and Pareto-optimal approach. It highlights the types of cell formation, their associated objectives, production parameters and production environments considered by various researchers. It also reflects the recent development on cell formation using multi-objective techniques including GA, SA, PSO and other heuristics methodologies that can handle more complex and realistic CFPs. DCF and Pareto-optimal approaches emerge as new trends in CMS. Inter-cellular parts movement and cell load variation received more importance than others.

The recent development shows that the multi-objective GA is considered as one of the most relevant techniques to solve both types of CFPs. A trend is also identified which shows that GAs can be implemented in combination with the others techniques like ANN, SA, cluster analysis, etc. These hybrid techniques are capable of finding superior results compared to simple GAs.

Some promising future research areas are also identified. These include workers assignment, uncertainties in parts/machines utilisation and demand variations. Cell layout design may be given more importance together with cell formation. Finally, industrial datasets may be considered to prove the efficiency of the proposed methods.

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