Materials Today: Proceedings 21 (2020) 66–72

Contents lists available at ScienceDirect

Materials Today: Proceedings

journal homepage: www.elsevier.com/locate/matpr

# Heuristic and meta-heuristic algorithms for solving medium and large scale sized cellular manufacturing system NP-hard problems: A comprehensive review

V. Kesavan [a], R. Kamalakannan [a,*], R. Sudhakarapandian [b], P. Sivakumar [c]

[a] Department of Mechanical Engineering, M.Kumarasamy College of Engineering, Karur 639113, India
[b] School of Mechanical Engineering, Vellore Institute of Technology, Vellore 632014, India
[c] Faculty of Engineering, MAHSA University, Malaysia

ARTICLE INFO

*Article history:*
Received 9 May 2019
Received in revised form 26 May 2019
Accepted 30 May 2019
Available online 10 July 2019

*Keywords:*
Cellular manufacturing systems
Cell formation
Layout problem
Alternate process route
Heuristic
Meta-heuristic algorithms

ABSTRACT

Shorter cellular manufacturing systems (CMSs) have emerged to cope with such production requirements and have been implemented with favourable results. Designing and implementing effective CMS involves many problems such as cell formation, machine layout, alternative process routes and inventory lot sizing. To review different heuristic, meta-heuristic, hybrid and exact solution algorithms developed to solve NP-hard problems associated with medium and large sized CMS problems. However, most of the researchers mainly focus on single optimization problem as multi-optimization results in poor performance. Hence, a robust meta-heuristic algorithm with hybridization is essential to address multiple CMS problems simultaneously.


## 1. Introduction

With spiraling demand for more mid-volume and medium variety of products with shorter life span, there is increasing burden on the producers to design effective products using better manufacturing systems. An effective manufacturing system consists of a number of cells each containing not more than 5 machines [2] for better productivity, production process, efficiency, efficacy, to reduce production cost etc., in order meet customer's demand on time [16,20]. Traditional cell manufacturing systems (CMS) such as functional layouts (job shops) and product flow layout (flow shops) cannot handle such high efficiency and efficacy as individually they consume high cycle time level and results in less flexibility and job satisfaction [16]. Hence Group Technology (GT) strategy was introduced in the recent years for achieving better production through cell manufacturing systems (CMS). GT in CMS aids to solve NP- hard problems by collating non-similar machines into manufacturing cells or machine groups and similar parts into part families. Such part families can be processed within single machine group [14] which forms the basis of effective production design and planning [16]. Similarly, GT helps to group production system into many distinguishable production cells to produce different parts from part families [2,14,20]. Also, it helps to group similar products requiring same process into families and produced in a cell consisting of functionally, non-similar machines, thereby enhancing production volume and solving long production times in batch manufacturing process by optimum use of machines or parts [2,23]. Since, large production volume is achieved through process and product grouping, CMS based on GT takes advantage of both product and functional layout by combining the efficiency of conventional flow shops with flexibility of job shops [2]. Recent days demand for more multifunctional manufacturing equipment and such needs are accomplished by processing production through multiple routes. Alternative process route enables efficient and flexible cell manufacturing system [25] by minimizing capital investment in machine, reducing intercellular movement of parts [4], better utilization of resources or machines and more number of independent cells [10]. Apart from reducing material flow by minimizing inter and intracellular movements, CMS with GT were developed to reduce process set up time. When similar tools or workers are grouped together, the set-up time decreases and batch-size reduce. It is important to achieve shorter set up time as it can affect batch size hence work-in-progress (WIP) levels.

* Corresponding author.
*E-mail address:* kamalbritto@yahoo.co.in (R. Kamalakannan).

https://doi.org/10.1016/j.matpr.2019.05.363
2214-7853/

For example, a production batch size can be reduced to 1 if the set up time is reduced to 0. With small batch sizes, parts do not travel far as machines are grouped together resulting in low WIP levels, in-process scheduling, material handling cost and lead times [2]. Therefore effective CMS design is required to improve throughput times, product quality and management systems and finally to achieve better production efficiency and floor control [2,14].

## 2. Problems faced by electronic manufacturing industries

In manufacturing industry, each cell contains several functionally dissimilar machines which can be used modified to be used in different operations. Such, production cells can be utilized to process production of various electronic goods. For effective functioning of these industries, it is important to group part types based on their similarities so that they can be effectively used in different processing lines such as fabrication, insertion, assembly, packaging etc. [16]. It is important to minimize intercellular movement of parts which is affected by a number of factors such as total number of parts present in the industry, number of batches, batch sizes, process sequence and routing[7].Therefore, designing an effective, real time applicable CMS involves many steps such as cell formation (CF), layout, alternative routing process etc., of which addressing cell formation problem (CFP) is the most important step [16,24]. CFP is a non-polynomial (NP) complex optimization problem [5], which involves the identifying and grouping machines and parts into cells and families with an objective to minimize inter and intra cellular movements [14]. Though CF can be both static and dynamic [24], with growing demand for effective machine and cells utilization, in a dynamic environment, were the production quantity does not necessarily equate to the demand, there can be increased demand for parts by various product mixes. This NP-hard problem can be overcome by integrating the CMS and Production Planning (PP) [28]. Production planning done beforehand in order to estimate and reconfigure the number and type of machines required to be placed for a particular period of time in a manufacturing cell [16,18] helps to optimize CF results by reducing production process time, cost involved in machine handling and labor, number of set-up required thereby enhancing product quality [7] however achieving such optimization using current algorithms might take long time and not necessarily result in better optimality [16].

Followed by CFP, the second most important step to be optimized is layout design, as it affects productivity of an organization. The different types of layout which requires to be optimized are machine and cell layout which includes both process and product layout respectively [21]. Modern days manufacturing process require optimization of machine layout problems (MLP) as a single machine may be required to perform multi functions by processing various parts to develop different products. Alternative processing routing is required as different parts in cells may have different sequence of operation due to the demands placed by various products [7]. Also, replication of machine is not possible or resolved to be last step in solving machine layout problem due to high capitalization cost of machine [16]. Hence, machine layout problem should be optimized to minimize intercellular movements of parts, machine coinciding and duplication [36,37] (Table 1).

The next NP-hard problem to solve in designing effective CMS is cell layout. A cellular layout consist of both product and process layout [21]. Grouping in cell layout enables collation of a set of machines with a number of components into unique machine-component cells so that process requirements of components in each machine cell is achieved within a cell [21], hence minimizing inter-cell movement of parts. The other problems include production, cell related costs, alternate routing, system reconfiguration, lot spitting and workload balance among machine and cells [16]. Fig. 1 represents different problems of CMS designing.

From literatures, it is understood that when researchers attempt to combine and solve CFP, MLP and cell layout problem (CLP) using single algorithm or approach, they mostly results in poor optimization and computational time. Hence, it is not advisable to solve multiple CMS problems through single approach. Sequencing of CMS problems results in better and effective CMS design [31]. Recently, several authors have preferred use of heuris-

**Table 1**
Problems in designing effective CMS.

| CMS designing problems |
|---|
| Cell Formation Problems (CFP) in which machine groups and part families are formed |
| Intra-cell or Machine layout determines the location of each machine in each cell |
| Inter-cell or Cell layout specifies the location of each cell |
| Group scheduling, lot splitting or workload balance |
| Resource (human, tool and materials) allocation problem. |
| Cell-related cost |

Source: Modified from Ameli et al. [1].

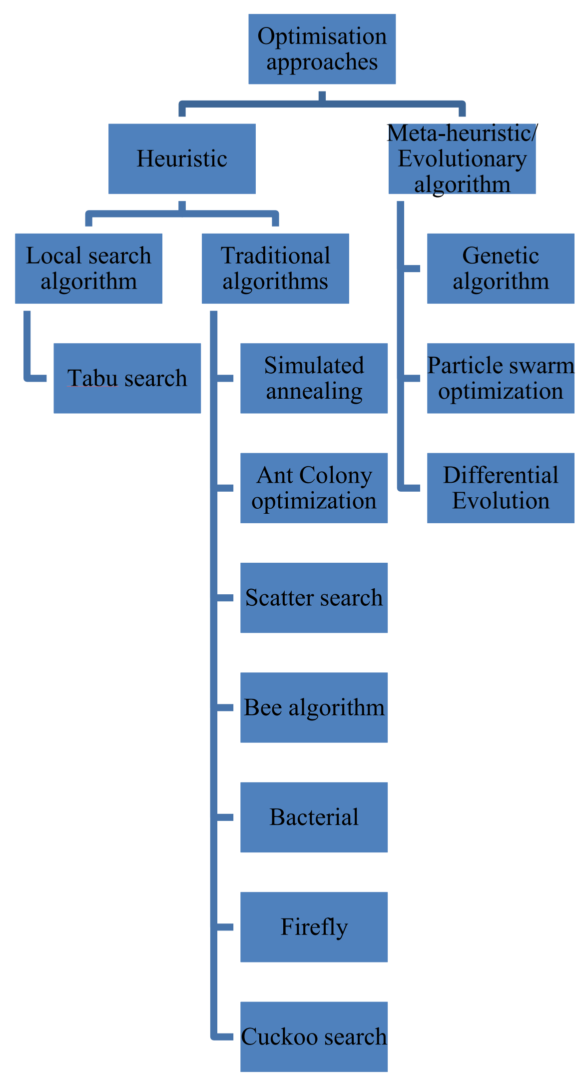


**Fig. 1.** Different optimization algorithms used in Cell Management Systems (CMS). Source: kamalakannan et al. [34,35].

tic or meta-heuristic algorithms against mathematical modelling in solving large complex problems of CMS [16]. Moreover, some researchers have even attempted to use meta-heuristic or hybrid algorithms in multi-objective optimization of CMS owing to its efficiency [14] which is also discussed in detail in this review [34,35] (Table 2).

## 3. Meta-heuristic algorithms

Meta-heuristic algorithms are derivatives of powerful heuristic algorithms, which on basis of heuristics methods, identify best possible solutions by guiding them over the search space [2].

### 3.1. Genetic Algorithm (GA)

One of the most widely used meta-heuristic algorithm in solving complex CMS problems is GA. GA was developed by Holland [8] on basis of natural evolution and genetics. It does intelligent random search within search space to solve NP- hard problems by providing best optimal solutions. GA starts with initial set of random population and each individual in the population analogy to behavior of chromosome, acts as solution of the object function. With search space, based on objective function each member of the population compete and select best neighbor. This process of selection is based on evaluation called as 'fitness function'. In concurrent steps, a new set of population is generated from crossover and mutation and the process continues to a set number of iterations known as 'stopping criterion' till best optimal solution is achieved.

The six steps of GA are as follows;

Step 1. Identification of initial population (random)
Step 2. Fitness function to evaluate each individual population
Step 3. Selection of best neighbor through search space
Step 4. Creation of new set of population by crossover
Step 5. Mutation of the population
Step 6. Iteration of steps based on stopping criterion till best optimal solution is achieved.

According to What is six sigma [31], performance of GA can be improved by choosing proper parameter values before implementing the algorithm. Since, grouping of machine and parts in manufacturing cells minimize cell idleness and enhance its efficiency, a GA was proposed were a special procedure was used to generate random initial population were one machine and one part is assigned to only one cell. Roulette Wheel selection procedure was used as selection strategy and for mutation, individuals are randomly chosen from the population in the proposed algorithm. When compared to grouping efficacy of ZODIAC, GRAFICS, GATSP, GA, EA and SA, the proposed algorithm showed better grouping efficacy in 6 problems and equivalent to best one in 11 problems [17]. Saraç and Ozcelik [26] developed a novel GA by combining different reproduction types with different crossover operators. Single, double and uniform crossover operators and roulette wheel, stochastic sampling and tournament was used in various combination to solve CFP and to maximize grouping efficacy. When compared with algorithms such as simulated annealing (SA), tabu search (TS), classic genetic algorithms with single point crossover, ant system (AS) and competitive neural network (CNN) developed by previous authors, the proposed algorithm showed equal grouping efficacy as best ones for 8 problems and improves grouping efficacy values for 6 problems. In order to address CF problem such as optimization of alternative processing route to minimize total intercellular movements of parts, process sequence and routing [7] developed a genetic algorithm heuristic and its optimization results was compared with existing algorithms such as SA, TS, fuzzy approach and similarity coefficient method and was reported to be better or comparable to the existing algorithms.

### 3.2. Particle swarm optimization algorithm (PSO)

Similar to GA, PSO is newly developed nature inspired, population-based local random search technique for addressing complex optimization problems. Developed by Kennedy and Eberhart [15] based on social interaction by flock of birds and school of fishes. The movement of the group or swarm is based on the leader's knowledge. Similarly, in PSO algorithm, solutions are obtained by following the best performer in the group. Being a member of swarm intelligence, it helps to solve continuous nonlinear problems [9]. Husseinzadeh Kashan et al. [9]. Developed a novel, discrete PSO, GBPSO algorithm based on grouping representation and grouping operation (group encoding) to solve cell formation problems. The proposed algorithms performance was compared against grouping genetic algorithm in 40 test problems. It was found that the developed algorithm gave better solution for 23 problems and for remaining 17 problem, the solution for both algorithms remained the same. Hence, for same population size and iteration, the optimal solution provided by GBPSO is more effective than GGA with minimal CPU time. However, hybridization of grouping genetic algorithm with a local search algorithm showed better solution against GBPSO hybridized with same local search. Similarly, Mahmoodian et al. [19] proposed a novel intelligent algorithm combining artificial individual intelligence and swarm intelligence, PSO and self-organization map (SOM) neural network (IPSO) for solving discrete CF problems. The proposed algorithm works in phases. Firstly, it trains network groups to learn on basis of distance measurement followed by second phase training were particles are directed to viable regions. The optimization results of the proposed algorithm was compared against standard PSO and best known solutions from literature for efficiency and efficacy. Though the developed algorithm was found to be effective. It had its own limitations such as the proposed algorithm does not provide optimal solution for cell clustering and has to be tested on larger problems.

### 3.3. Hybrid algorithm

Pachayappan and Panneerselvam [21] proposed a hybrid genetic algorithm (HGA) were the initial population was generated randomly using ideal seed heuristic and fitness function value of each chromosome was evaluated. Crossover and mutation process was applied on the subpopulation to produce offspring and their fitness function value was assessed. This process was repeated till best fitness function value among machine-component is selected and implemented. It provided better grouping efficiently and grouping efficacy when compared to ZODIAC and GRAFICS algorithms. A hybrid grouping genetic algorithm (HGGA) developed by James et al. [11] local search with a standard grouping genetic algorithm to solve machine-part cell formation problem (MPCF). Selection is based on rank based roulette wheel selection, along with the GGA 2 point crossover operator with repair heuristic. No mutation operator was used. 35 problems were identified from literature and tested for HGGA against ZODIAC, GA, MST-Clustering Algorithm, GRAFICS, GATSP, genetic programming (GP) and evolutionary algorithm (EA). When compared to GGA, HGGA performs best in 30 problems and similar to GGA in 5 problems. The HGGA performs equivalent to other algorithms. Though EA showed better performance on few problems when compared to the HGGA due to rounding, data inconsistencies and few single reported studies on EA lead to poor comparison of the EA against hybrid grouping genetic algorithm.

**Table 2**
Different heuristic and meta-heuristic algorithms developed to solve CMS NP-hard problem.

| Author and Year | Proposed Algorithm | Problems addressed in CMS | Compared algorithms | Total number of problems | Total number of problems with best solution | Total number of problems with equivalent solution |
|---|---|---|---|---|---|---|
| Mahdavi et al. [17] | GA with Roulette Wheel selection procedure and randomly chosen individual for mutation | Cell layout – grouping efficacy | ZODIAC, GRAFICS, GATSP, GA, EA and SA | 17 | 6 | 11 |
| Saraç and Ozcelik [26] | GA working with different crossover operators (single-point, double-point and uniform) and reproduction types (roulette wheel, stochastic sampling and tournament) | Cell formation – grouping efficacy | SA, TS, original GA with single point crossover, AS and CNN | 14 | 8 | 6 |
| Hazarika and Laha [7] | GA | Cell layout – intercellular movements | SA, TS, fuzzy approach, similarity coefficient method | – | – | – |
| Husseinzadeh Kashan et al. [9] | GBPSO algorithm based on grouping representation and grouping operation | Cell formation problems | GGA | 40 | 23 | 17 |
| Mahmoodian et al. [19] | IPSO – PSO with SOM neural network | Discrete CF problems | PSO | – | – | – |
| Pachayappan and Panneerselvam [21] | HGA with ideal seed heuristic | CF problem | ZODIAC and GRAFICS | – | – | – |
| James et al. [11] | HGGA with local search. rank based roulette wheel selection and 2 point crossover operator with the repair | Machine-part cell formation problem (MPCF). | ZODIAC, GRAFICS, MST, GATSP, GA, GP and EA | 35 | 30 | 5 |
| Wu et al. [32] | SACF | CF problem for grouping efficacy | ZODIAC, TSP-GA GA | 25 | 18 | 6 |
| Jouzdani et al. [12] | SA with local search | Cellular layout – inter and intra-cellular movements; set up cost, alternative routing | SA, BB | 10 | – | – |
| Wang et al. [30] | SSPPO | cell formation and parts scheduling problem (CFPSC) | SSSPT, SSODD and SSFIFO | 12 | – | – |
| Ameli et al. [1] | MOSS | cell formation and layout design problems | Epsilon constraint and NSGA-II. | – | – | – |
| Bajestani et al. [3] | MOSS along with MADM technique (TOPSIS) | dynamic cell formation problem along with cell load variation and cost minimization | SPEA-II and NSGA-I | 10 | – | – |
| Solimanpur et al. [27] | ACO | Sequence, production volume problems along with minimizing intercellular movements and voids | CLASS, clustering, minimum spanning tree, GA, neural network | 8 | 4 | 4 |
| Kamalakannan et al. [13] | ACO | MPCF | ZODIAC, GRAFICS, MST-Clustering Algorithm, GATSP, GA & EA. | 16 | 5 | 8 |
| Karoum et al. [14] | CS along with Local search | CFP | ZODIAC, GRAFICS, EA, SA, GRASP heuristic, GA and large neighbour search (LNS) | 35 | 31 | 4 |
| Tavana et al. [29] | DCOA along with GT | resource allocation, manufacturing cost and system productivity problems | FF, RR and GA | 40 | – | – |
| Gómez et al. [6] | TS with multithread processing | CFP | TS | 11 | 5 | 3 |
| Papaioannou and Wilson [22] | TS with short-term memory and overall iterative searching strategy | CFP | Mixed integer linear programming | – | – | – |

Source: kamalakannan et al. [34,35].

### 3.4. Simulated annealing

Developed by Kirkpatrick et al, SA is a powerful heuristic method which avoids local minimum by jumping to higher energy state until best solution is found in search spaces. Unlike other heuristic and meta-heuristic methods, SA proves to be an effective and easy to implement multi-objective algorithm to address multiple optimization problems. Developed SA algorithm for CF problem (SACF) was the number of cells resulting in the best grouping efficacy is generated automatically, or users are given the flexibility to choose the number of cells they prefer. Also, additional indicators are used to speed up the search process in local optima. 25 problems from literature were identified and tested against ZODIAC, TSP-GA and GA algorithms. It was found that the proposed algorithm showed improved group efficacy values in 18 and equivalent values in 6 problems respectively.

In its first attempt to consider inter and intra-cellular movements based on operation sequence, and setup costs along with alternative routings and machine reliability [12] developed an SA algorithm with a local search procedure. Out of 4 problems identified from the literature and 6 randomly generated test problems, the computational results were comparable with original SA and Branch and Bound (BB) method. Apart from its efficiency and efficacy calculation, time spent on obtaining solution and quality of solution obtained was difficult to compare.

### 3.5. Scatter search

SS is a heuristic proposed by Grover in 1977 were non-random solutions are generated. Instead of working on a single solution, similar to other evolutionary based algorithms, it embeds a set of combined solutions to construct new solutions. This initial set of solutions is obtained from prior problem solving memory and not only based on objective function values. Though Tabu Search (TS) metaheuristic and SS share same origin, as both derive at solutions based on memory, it was initially assumed that SS was a process available inside the framework of TS. However, over past decade, SS has received considerable attention from researchers as it is a flexible meta-heuristic approach which can incorporate a number strategies like local search, TS etc. to solve complex problems [30]. Wang et al. [30] Developed SSPPO a scatter search (SS) algorithm combining different dispatching rule such as Processing time (PT), PW and Operation Due Date (ODD) and compared its performance with other SS algorithms with dispatching rules like Shortest Processing Time (SPT), First In First Out (FIFO) and Operation Due Date (ODD) namely, SSSPT, SSODD and SSFIFO respectively to solve2 joint problems namely CF and parts scheduling (CFPSC). CFPSC is a nonlinear mixed integer programming model were a number of machine and parts required for batch processing is identified and sequenced to increase productivity and reduce penalty cost. When tested on 12 problems, it was found that SSPPO provided least penalty cost and achieved better solutions with reasonable computational time. To test the efficacy of the proposed model, solution combination methods and improvement methods was used namely BCM, CCM, FIM and SIM to form 4 different SSPPO namely SSPPO-BF, SSPPO-CF, SSPPO-BS and SSPPO-CS). Low computation time was given by SSPPO-BS and SSPPO-CF gave least penalty cost.

To solve cell formation and layout design problems of CMS, Ameli et al. [1] proposed a multi-objective scatter search (MOSS) algorithm. The computational results of the proposed algorithm was compared against multi-objective evolutionary algorithm (MOEA), and non-dominated sorting genetic algorithm II (NSGA-II). It was reported that the developed MOSS algorithm produces optimal solutions for small-sized problems and performed better than NSGA-II.

Another multi-objective scatter search (MOSS) given by Bajestani et al. [3] aims to address dynamic CFP along with cell load variation to minimize cost involved. The proposed model was tested against two different meta-heuristic algorithms namely, NSGA-I and Strength Pareto evolutionary algorithm (SPEA-II). It was found that the developed algorithm outperforms the two meta-heuristic algorithms. Moreover, when Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and multi-attribute decision making (MADM) techniques was applied, it enabled decision makers to define attribute weights by specifying whether diversity is more important or proximity in the proposed algorithm.

### 3.6. Ant colony optimization (ACO)

Dorigo and Caro developed ACO, a mathematical analogy to behavior of the real ants based on probabilistic technique. Real ants in search of food, leave their colony and find the optimal or shortest part to reach the food and carry it back to its nest. As ants are blind, when they leave their nest, they secrete a chemical called pheromone along their path in search of food. The following ants also secrete this substance and the path with optimal distance has high pheromone when compared to other paths. Posterior ants simply follow the path with high pheromone to reach their objective at shortest time [27]. Solimanpur et al. [27] gave a novel model ACO algorithm, to solve sequence and production volume problems to minimize intercellular movements of parts and idleness in CMS. 8 problems were identified from literature and the results of the proposed algorithm was evaluated against cell and layout solution using sequence data (CLASS), clustering, minimum spanning tree, GA, neural network. It was found that the proposed algorithm showed better improvement in 4 problems and equivalent to 4 problems.

Another work by [13] used single objective ACO algorithm to solve MPCF problem. Machine index based local search procedure was used to enhance group efficacy. Termination criteria were set at 1000X number of iterations, and sensitivity analysis was conducted to identify the best suitable value of evaporation factor. 16 problems were identified from the literature, and the results of the proposed algorithm was tested against ZODIAC, GRAFICS, MST-Clustering Algorithm, GATSP, GA & EA. It was observed that ACO algorithm showed better grouping efficacy in 5 problems, equivalent to 8 problems and performed poor grouping of 3 problems.

### 3.7. Cuckoo search algorithm (CS)

CS algorithm is yet another nature inspired, global optimisation, meta-heuristic algorithm developed based on lifestyle and parasitic behavior of some cuckoo bird species which mimick eggs of chosen host birds and lay their eggs in host nest [33]. Developed by Xin-She Yang and Deb in 2009, it helps to solve multimodal functions based on 3 rules. Similar to other evolutionary algorithms, CS starts with initial population were each egg in a nest represents a solution and cuckoo egg represents good solution. As a cuckoo lays an egg, it places it in a randomly chosen nest. Nest with high number of quality eggs (solutions) gets iterated to next generations. Finally, as the number of host nests is fixed the chances of host discovering alien egg is at probability of pa $\in$ [0,1]. Discovery occurs in worst nest whose solutions are dumped [14]. Karoum et al. [14] Proposed a modified CS algorithm by combining local search approach as it is simple and use the same measure to intensify search and generate good results to solve manufacturing cell formation problem. The obtained results were compared with algorithms like ZODIAC, GRAFICS, evolutionary, simulated annealing, GRASP heuristic, GA and large neighbourhood search (GA-LNS). The proposed model provided the best solution for 31problems out of 35 test problems (88.57%). However, the proposed method was not assessed for other cell formation problems such as parts routing number and applicable manufacturing data. Tavana et al. [29]. Developed a discrete cuckoo optimization algorithm (DCOA) based on grouping technology to solve large sized resource allocation problems, reduce manufacturing cost and increase system productivity. The efficiency and efficacy of the proposed algorithm was tested on 40 test problems and compared with first fit (FF), round robin (RR) and GA algorithm. It was reported that the developed algorithm performance was equivalent to GA in large sized problems.

### *3.8. Tabu search strategy (TS)*

Developed by Glover in 1986 to solve finite solution set optimization problems. It is a meta-heuristic which aids local search heuristic by finding solution through dynamic neighborhood search using tabu list. The tabu list restrict movement to areas which was previously explored based on its memory structure. These memory structures store a list of searches made previously during the process which can be used to intensify or diversify search in space [6]. Gómez et al. [6] proposed a tabu search with multithread processing to explore optimum local areas in solving CFP. The proposed model was tested against other tabu search strategies developed in two kinds of literature. It was observed that for 11 problems identified from literatures, the proposed strategy produced best solution for 5 problems and 3 equivalent solutions. For rest of the problems, the proposed strategy showed the poor solution. Another experiment by Papaioannou and Wilson [22] uses short-term memory and overall iterative searching strategy TS with simple search process to solve real time machine-part grouping problems of cell formation. The performance was computed along with mixed integer linear programming and was found to be promising for larger datasets.

## 4. Discussion

Though many nonlinear mathematical model are developed and applied for small size CMS problems, they are not suitable for addressing large sized, real-time, NP-hard problems observed in designing an effective CMS. Hence, many researchers have resolved to develop algorithms which could address problems such as cell formation, layout problems, resource allocation, costing etc. Mahdavi et al. [17] used genetic algorithm to address cell layout issue in CMS. It was reported that out of 22 problems identified from literature the proposed model showed best grouping efficacy for 6 problems, good solution for 11 problems and equivalent grouping efficacy for 5 problems against algorithms like ZODIAC, GRAFICS, GATSP, GA, EA and SA proposed in previous literatures. Similarly, Saraç and Ozcelik [26] developed GA with different crossover operators and reproduction types to solve cell formation problem by maximizing grouping efficacy, it was found that the developed model showed better grouping efficacy in 6 problems and equal efficacy in 8 problems with 1 exception. Also work by Hazarika and Laha [7] showed better or equivalent approach based on GA for optimizing intercellular movements of parts and best route selection against well-known conventional models. Therefore, it can be concluded that GA is better meta-heuristic algorithm to solve CFP. However, choice of operators and parameters plays major role in obtaining better performance of the GA in solving CMS problems. Similarly, the above studies have focused on single optimization instead of focusing on multi-optimization such as cell formation and cell layout problems. Hence, for effective CMS designing, GA along with other heuristic algorithm can be used to address multi CMS problems simultaneously.

Similar to GA, PSO has been proposed by many researchers to address CMS issues mainly cell formation problem. GBPSO proposed by Husseinzadeh Kashan et al. [9] combines PSO with grouping technology. When tested its performance against GGA using 40 test problems identified from the literature, it was found that GBPSO was able to provide better grouping efficacy in 23 problems and equal solution to 17 problems, however, the results were not significant enough to conclude that PSO is better than GA in addressing CFP. Another work by [19] which only compared the efficacy of the developed algorithm IPSO against semi-PSO and ordinary PSO to solve discrete CF problem in 30 identified problems, the study reported both developed, and semi-PSO showed better solutions for the identified issues. Hence, it can be concluded that both PSO and GA offer a better solution for CFP in effective CMS designing. Pachayappan and Panneerselvam [21] Hybrid GA with ideal seed heuristic showed better and equivalent group efficiency and group efficacy in 24 literature identified test problems against ZODIAC, GRAFICS, Algorithm I and Algorithm II. Similarly, hybrid GGA with 2 point crossover operator, showed the better solution in 30 problems and equivalent solution in 5 problems in MPCF problems against ZODIAC, GRAFICS, MST, GATSP, GA, GP and EA. Hence, it can be concluded that hybridization of GA produces better results than ordinary GA and group GA.

Against 25 identified test problems, the proposed SA developed by researchers Wu et al. [32] except 1, enhance grouping efficacy in 18 problems and achieve an equivalent solution in 6 problems when compared to well-known algorithms such as ZODIAC and TSP-GA and GA. Similarly, SA with local search was used to address multiple problems such as layout and alternate routing, however, the results achieved is not better than original SA and BB when compared against 10 literature identified problems. Hence, hybrid SA is not effective in addressing multi CMS problems.

Several researchers have used SS to address multi problems of CMS such as cell formation along with layout or scheduling or load variation or cost minimization Wang et al. [30,1], Bajestani et al. [3]. Though studies have identified 10–12 problems from literature and compared its performance against previously developed SS or evolutionary algorithm and genetic algorithm, the studies have not reported its efficacy or efficiency against compared models numerically. Hence, it can be concluded that SS is best for multi optimization however as the complexity increases, its performance is indeterminate.

ACO is used by researchers for single and multi-optimization. Solimanpur et al. [27] Developed ACO to address both sequence and intercellular movement problems. When tested its performance against 8 literature identified problems and well known algorithms such as CLASS, clustering, minimum spanning tree, GA, neural network, it was found that 4 problems were given best solution and 4 equivalent solution. Hence, ACO is equivalent in its performance when compared to other meta-heuristic approaches such as GA and neural network. Another work by Kamalakannan et al. [13] which used ACO to address MPCF problem alone reported that out of 15 test problems, best solution was given to 5 problems when compared against ZODIAC, GRAFICS, MST-Clustering Algorithm, GATSP, GA & EA. Hybrid Cuckoo search is used by researchers to address CFP and resource allocation problems[14,29]. When compared to algorithms like GA, FF, RR, ZODIAC, GRAFICS, EA, SA, GRASP heuristic, GA and large neighbour search (GA-LNS), hybrid CS produce better efficiency and efficacy against large complex test problems.

## 5. Conclusion

From the above review, it can be concluded that meta-heuristic algorithms such as GA, PSO, CS offer better grouping efficiency and efficacy for discrete NP-hard cell formation problems. However, most of the researchers mainly focus on single optimization problem as multi-optimization results in poor performance. Hence, a robust meta-heuristic algorithm with hybridization is essential to address multiple CMS problems simultaneously.

## 6. Future scope

Hence, it was concluded that developing an algorithm to solve multiple realistic, complex model is very costly and close to impossible as it has to consider the following factors; multiple machines of identical type, an unknown number of machines which should be considered as model variables and an unknown number of cells. Similarly, human resource planning and scheduling should also be considered. Hence, a multi-objective model should be developed in the near future considering material handling costs, resource allocation cost which includes human, reliability costs, etc.

## References

[1] M.S.J. Ameli et al., Cell formation and layout design with alternative routing: a multi-objective scatter search approach, Int. J. Ind. Syst. Eng. 14, 3 (2013) 269.
[2] V. Anbumalar, M. Raja Chandra Sekar, Methods for solving cell formation, static layout and dynamic layout cellular manufacturing system problems: a review, Asian J. Sci. Technol. 6 (12) (2015) 2107–2112.
[3] M.A. Bajestani et al., A multi-objective scatter search for a dynamic cell formation problem, Comput. Oper. Res. 36 (3) (2009) 777–794.
[4] D. Cao et al., Grouping operations in cellular manufacturing considering alternative routings and the impact of run length on product quality, Int. J. Prod. Res. 47 (4) (2009) 989–1013.
[5] C. Dimopoulos, A.M.S. Zalzala, Recent developments in evolutionary computation for manufacturing optimization: problems, solutions, and comparisons, IEEE Trans. Evol. Comput. 4 (2) (2000) 93–113.
[6] A.T. Gómez et al., Cell formation problem: an multithreading tabu search for setup time optimization for limited machine magazines – a new solution for a classical problem, in: Proceedings of the 11th International Conference on Informatics in Control, Automation and Robotics, SCITEPRESS - Science and Technology Publications, 2014, pp. 332–339.
[7] M. Hazarika, D. Laha, Genetic algorithm approach for machine cell formation with alternative routings, Mater. Today Proc. 5 (1) (2018) 1766–1775.
[8] J.H. Holland, Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence, U Michigan Press, England, 1975.
[9] A. Husseinzadeh Kashan et al., A novel discrete particle swarm optimization algorithm for the manufacturing cell formation problem, Int. J. Adv. Manuf. Technol. 73 (9–12) (2014) 1543–1556.
[10] H. Hwang, P. Ree, Routes selection for the cell formation problem with alternative part process plans, Comput. Ind. Eng. 30 (3) (1996) 423–431.
[11] T.L. James et al., A hybrid grouping genetic algorithm for the cell formation problem, Comput. Oper. Res. 34 (7) (2007) 2059–2079.
[12] J. Jouzdani et al., applying simulated annealing to a generalized cell formation problem considering alternative routings and machine reliability, Asia-pacific J. Oper. Res. 31 (4) (2014) 1450021.
[13] R. Kamalakannan et al., An ant colony optimization algorithm for cellular manufacturing system, Appl. Mech. Mater. 854 (2016) 133–141.
[14] Karoum, B. et al.: Manufacturing Cell Formation Problem Using Hybrid Cuckoo Search Algorithm. Presented at the (2018).
[15] Kennedy, J., Eberhart, R., A discrete binary version of the particle swarm algorithm, in: Proceedings of the conference on systems, man and cybernetics.
[16] A.S. Kheirkhah, A. Ghajari, A three-phase heuristic approach to solve an integrated cell formation and production planning problem, Uncertain Supply Chain Manag (2018) 213–228.
[17] I. Mahdavi et al., Genetic algorithm approach for solving a cell formation problem in cellular manufacturing, Expert Syst. Appl. 36 (3) (2009) 6598–6604.
[18] I. Mahdavi et al., Multi-objective cell formation and production planning in dynamic virtual cellular manufacturing systems, Int. J. Prod. Res. 49 (21) (2011) 6517–6537.
[19] V. Mahmoodian et al., A novel intelligent particle swarm optimization algorithm for solving cell formation problem, Neural. Comput. Appl. (2017).
[20] M. Mohammadi, K. Forghani, A dynamic programming–enhanced simulated annealing algorithm for solving bi-objective cell formation problem with duplicate machines, Decis. Sci. Lett. 4 (2) (2015) 261–276.
[21] M. Pachayappan, R. Panneerselvam, Hybrid genetic algorithm for machine-component cell formation, Intell. Inf. Manag. 7 (3) (2015) 107–122.
[22] G. Papaioannou, J.M. Wilson, A tabu search algorithm for the cell formation problem with part machine sequencing, Found. Comput. Decis. Sci. 37 (2012) 2.
[23] G. Prabhakaran et al., Machine cell formation using simulated annealing algorithm in cellular manufacturing system, Int. J. Comput. Aided Eng. Technol. 10 (1/2) (2018) 111.
[24] R. Raminfar et al., A mathematical programming model for cell formation problem with machine replication, J. Appl. Math. 2013 (2013) 1–9.
[25] M. Saeed Jabal Ameli, J. Arkat, Cell formation with alternative process routings and machine reliability consideration, Int. J. Adv. Manuf. Technol. 35 (7–8) (2008) 761–768.
[26] T. Saraç, F. Ozcelik, A genetic algorithm with proper parameters for manufacturing cell formation problems, J. Intell. Manuf. 23 (4) (2012) 1047–1061.
[27] M. Solimanpur et al., Solving cell formation problem in cellular manufacturing using ant-colony-based optimization, Int. J. Adv. Manuf. Technol. 50 (9–12) (2010) 1135–1144.
[28] R. Tavakkoli-Moghaddam et al., Reliability optimization of series-parallel systems with a choice of redundancy strategies using a genetic algorithm, Reliab. Eng. Syst. Saf. 93 (4) (2008) 550–556.
[29] M. Tavana et al., A discrete cuckoo optimization algorithm for consolidation in cloud computing, Comput. Ind. Eng. 115 (2018) 495–511.
[30] X. Wang et al., A scatter search approach with dispatching rules for a joint decision of cell formation and parts scheduling in batches, Int. J. Prod. Res. 48 (12) (2010) 3513–3534.
[31] Whatissixsigma: Introduction to cellular manufacturing system problems.
[32] T.-H. Wu et al., A simulated annealing algorithm for manufacturing cell formation problems, Expert Syst. Appl. 34 (3) (2008) 1609–1617.
[33] X.-S. Yang, Suash Deb, Cuckoo Search via Lévy flights, in: 2009 World Congress on Nature & Biologically Inspired Computing (NaBIC), IEEE, 2009, pp. 210–214.
[34] R. Kamalakannan, R. Sudhakara Pandian, A Tabu search strategy to solve cell formation problem with ratio level data, Int. J. Business Intel. Data Min. 13 (1/2/3) (2018) 209–220.
[35] R. Kamalakannan, R. Sudhakara Pandian, A Simulated annealing for the cell formation problem with ratio level data, Int. J. Enterprise Network Manage. 10 (1) (2019) 78–90.
[36] S. Saravanan, A. Godwin Antony, V. Vijayan, M. Loganathan, S. Baskar, Synthesis of $SiO_2$ nano particles by using sol-gel route, Int. J. Mech. Eng. Technol. 1 (2019) 785–790.
[37] S. Dinesh, A. Godwin Antony, K. Rajguru, V. Vijayan, Experimental investigation and optimization of material removal rate and surface roughness in centerless grinding of magnesium alloy using grey relational analysis, Mech. Mech. Eng. 21 (2017) 17–28.