MultiCraft

International Journal of Engineering, Science and Technology
Vol. 2, No. 5, 2010, pp. 198-215

INTERNATIONAL JOURNAL OF ENGINEERING, SCIENCE AND TECHNOLOGY
www.ijest-ng.com

Genetic rule based techniques in cellular manufacturing (1992-2010): a systematic survey

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Abstract

Genetic algorithm is believed to be the most robust unbiased stochastic search algorithm for sampling a large solution space. Considering the steady convergence framework of genetic algorithm, it is intensely recognized in group technology applications in cellular manufacturing, and subsequently employed in part family construction, machine cluster formation and manufacturing cell designing since preceding two decades. This study demonstrates a substantial description of various genetic algorithm based techniques and its usage in manufacturing cell design problem and categorically emphasizes on the significance of the prompt propagation of genetic algorithm in cellular manufacturing and its empirical modifications in genetic operations which are evolving as an indispensable segment of managerial decision making. The sustained growth of genetic algorithm and its intricate practices such as managing multi-objective problems and forming hybrid procedures are the focus areas of this article. The major verdict of this research work is to identify the trend of genetic algorithm in cellular manufacturing system, which was started with very basic simple genetic algorithm in 1990 and gradually evolved with complex hybrid techniques in recent time.

Keywords: Cellular manufacturing, group technology, genetic algorithm, survey, review

1. Introduction

In nature individuals are generally harmonized to their surroundings in order to persist in evolution process, in which reproduction conserves those features which make an individual capable enough to compete successfully (Darwin, 1929), therefore the fragile characteristics are ruined consequently. *Genes* are such units which regulate dominating characteristics by forming sets identified as *chromosomes.* Over subsequent generations not only the stronger individuals survive, but also their fittest genes which are transmitted to their descendants during the recombination process namely *crossover*. Metaphors between the mechanism of natural selection and optimization process motivated the evolution of Genetic Algorithm (GA), in which the main objective is to simulate the evolutionary process through computer.

Thematically in cellular manufacturing systems (CMS), group technology (GT) could be projected as a manufacturing metaphysics which recognises similar parts, therefore associating them into part families depending on its manufacturing designs, characteristics and geometric shapes which was first introduced by Burbidge (1963, 1971, 1975). GT is employed in CMS to develop an alternative of conventional manufacturing system. Designing manufacturing cell has been called cell formation problem (CF/CFP). It consists of the following courses: usually similar parts are grouped into part families following their processing requirements, and diverse machines are grouped into manufacturing cells and subsequently part families are designated to cells. The problem encountered in CMS is construction of such cells irrespective of its type (Selim *et al.*, 1998). Not essentially the aforementioned steps are carried out in the above order or even gradually. Depending upon the procedures involved in CFP three methods of achieving solutions are proposed (Papaioannou and Wilson, 2010): (1) recognizing part families first and consequently machines are clustered into cells depending on the processing requirement of part families, (2) recognizing manufacturing cells by grouping heterogeneous machines and then the part families are allocated to cells, (3) part families and machine cells are developed concurrently.

Researchers of Cellular manufacturing are constantly addressing problems for which conventional problem solving techniques are not reliable owing to their higher computational complexities towards convergence. CMS being difficult to systematize mathematically, many researchers have considered non-conventional techniques such as heuristics, metaheuristics and artificial intelligent techniques such as neural networks and fuzzy set theory to solve CFPs in order to achieve optimal solutions. Genetic Algorithm (GA) is reported as a competent alternative in such categories. In the literature of CFP (Papaioannou and Wilson, 2010) the research trend is found in practicing artificially intelligent methodologies, due to their strong nature of converging to attain optimal solution than that of the conventional methods.

The prime objectives of this study are to: (1) introduce a comprehensive description of Genetic Algorithm (GA), (2) review published literature of CFP based on GA methods, (3) to conduct an analytical study based on aforesaid review and (4) to indicate the possible scope of prospective research.

2. An Overview of Genetic Algorithm

Genetic algorithm is a widespread, parallel, stochastic search and optimisation method, grounded on the perspectives of natural selection (Darwin, 1929) and population genetics (Fisher, 1930). In general, any recursive, population based method that uses selection and random variation to generate new offspring can be widely disposed as genetic algorithm. Holland (1975) first proposed GA and Goldberg (1989) further made this algorithm accustomed among researchers. It is a model of machine learning which derives its behaviour from a metaphor of the processes of evolution in nature. GA is executed iteratively on a set of coded chromosomes, called a population, with three basic genetic operators: selection, crossover and mutation. Each chromosome is represented by a string, which could be binary or real coded. GA utilizes only the objective function information and probabilistic transition rules for genetic operations. Crossover is the elementary operator of GA. The essential steps of a GA (Figure 1) are reported in pseudocode 1. A comprehensive theory of GA can be studied from the book composed by Gen and Cheng (2000). An elaborated discussion of GA and its practice in CFP is contributed accordingly in next subsections.

Due to the strong competency to obtain optimal solution, GA is heavily adopted in diverse industrial optimization problems which are non-linear in nature. Genetic Algorithms could be used for numerous scheduling problems, which enable relatively arbitrary constraints and objectives to be incorporated into a single optimization method (Man *et al.*, 2008; Shaw *et al*., 1999; Xing *et al.*, 2007). In robotics human designers and engineers develop machines which are proficient to perform human work. GAs can be programmed to search for a range of optimal designs and components for each specific use, or to return results for entirely new categories of robots that can perform multiple tasks and have more general application (Mucientes *et al.*, 2007; Nelson *et al.*, 2009; Fravolini *et al.*, 2003). GAs are being utilized for dynamic and anticipatory routing of circuits for telecommunications networks. Other GA based applications are being developed to optimize placement and routing of cell towers for best coverage and ease of switching (Rango *et al.*, 2007; Zhengying *et al.*, 2001; Bari *et al.*, 2009). Genetic Algorithm could also be used for designing composite materials and aerodynamic shapes of vehicles and transporters, which can enhance the speed and can minimize the weight, fuel consumptions and risk of the vehicles (Rajendran, and Vijayarangan, 2001). Application of GA can also be found in supply chain network design problems (Altiparmak *et al.*, 2006), structural and operational design of buildings, factories, machines (Bullock, 1995), in modelling of finance and investment strategies (Markowska-Kaczmar *et al.*, 2008) and many other emerging industrial sectors including cellular manufacturing since last few decades.

3. Application of Genetic Algorithm in Cellular Manufacturing

Venugopal and Narendran (1992), Gupta *et al.* (1996), Hsu and Su (1998) and Chan *et al.* (2004) implemented GA as a multi-objective solution methodology and solved diverse objectives such as total movements of components, count of EEs, Voids and cell load variation. Joines *et al.* (1996) developed a GA using new chromosome representation which reduced the size of the model; hence demonstrated efficiency by comparing the maximum number of states visited by the technique. Morad and Zalzala (1996) proposed genetic-based methods to solve the CFP in CM and the batch scheduling problem, they reported that the processing parameters do affect the formation of cells. Hwang and Sun (1996) developed globally efficient two-phase GA-heuristic for CFP considering intercell move factors. Zhao *et al.* (1996) introduced fuzzy clustering method for in-exact real-data structure and proposed GA due to its population-wide and stochastic nature. Whereas Chi and Yan (2004) and Pai *et al.* (2005) attempted to test GA in fuzzy environment speculating the manufacturing factors such as multi-process plan, alternative routing of parts, fuzzy product demands and fuzzy technical feasibility of machines. Another method, known as integer-coded GA was proposed by Tavakkoli-Moghaddam *et al.* (2007) to handle the uncertainty in fuzzy environment. Al-Sultan and Fedjki (1997) stated a genetic-operator-based heuristic method and tested the aforementioned technique with previously proposed methods with prospective solutions.

Pierreval and Plaquin (1998, 2000) suggested an NPEA, which demonstrated a set of non-dominated solutions with respect to several objectives and further investigated on EA based on four constraints criteria: bounded size of cells, the machines which must stay together, and the machines which should not stay together, the machines around which the cells have to be formed, and they reported faster convergence characteristics of the proposed technique. Gravel *et al.* (1998) presented a double-loop GA method which could be used to make the best use of the existing cell design by routing parts through the cells efficiently. Moon and Gen (1999) and Kazerooni *et al.* (1997) both considered Production volume, machine capacity, processing time and sequence, number of cells and cell sizes and alternative routing, and therefore the proposed solutions depicted encouraging result. Zhao and

Wu (2000) used multi-objective modified-GA and found the technique is completely feasible for mid-size problems with moderately higher execution time. Mak and Wong (2000) implemented a genetic CFP model based on total cell flows and further ANOVA technique is introduced to select the appropriate system parameters. On the other hand Zolfagharia and Liang (2003, 2004) considered processing time, lot size, and machine capacity and used multi-factor ANOVA, and the study reported significant improvement by indicating the importance of GA parameters selection and the authors further experimented with generalized grouping efficacy index compared with conventional measures and stated that GA is best-fit with larger population size and lower mutation rate.

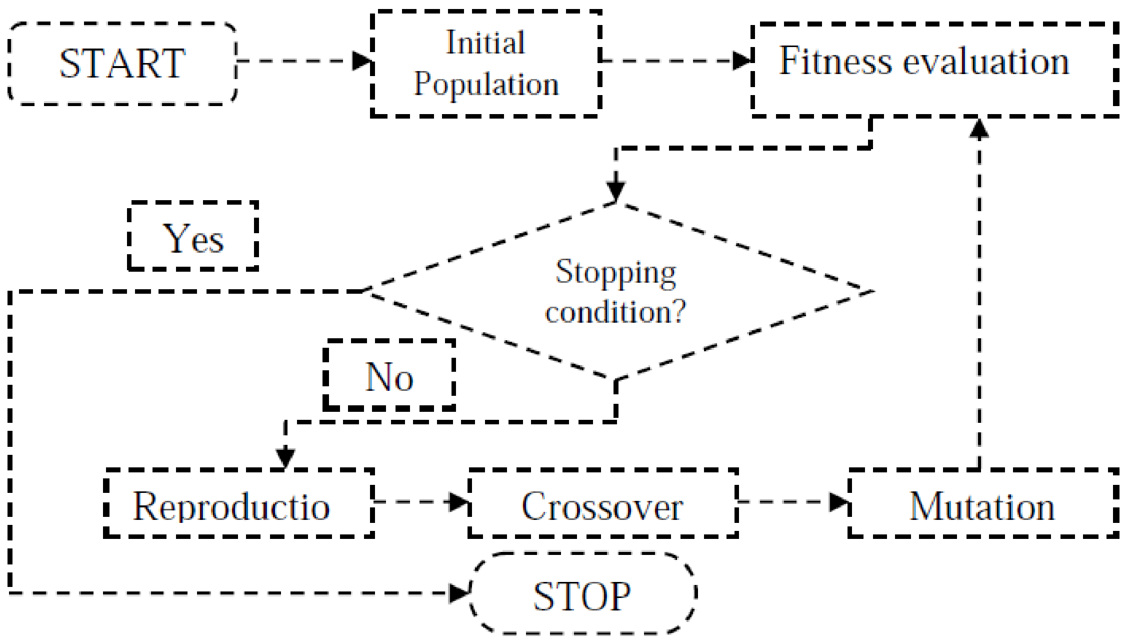

Figure 1. Genetic Algorithm

Mak *et al.* (2000) suggested an adaptive scheme based genetic search technique to solve CFP which maximized bond energy measure to some extent. Anita Lee-Post (2000) efficiently used SGA with GT coding system (DCLASS) to cluster part families which is well suited for part design and process planning in production process. Chu and Tsai (2001) proposed a GA based heuristic technique and a new similarity coefficient method to adjust the gene value of each part. However Wu *et al.* (2002) proposed a new group mutation operator to increase the mutation probability, and with the help of two-layer hierarchical chromosome structure the CFP and machine layout problems are simultaneously solved.

Pseudocode 1: Genetic Algorithm (GA)

```
Initialize;
Repeat
        Evaluate the individual chromosome;
        Repeat
            Select parents using specific selection strategy;
            Generate offspring using crossing over operation;
            Mutate if enough solutions are generated;
        Until population number is reached;
        Copy the best fitted individuals into population as they were;
Until required number of generations are generated.
```

Further GA-embedded heuristic-inspired-mutation is introduced by Mahdavi *et al.* (2009), which is to produce significantly improved solution. Brown and Sumichrast (2001), Filho and Tiberti (2006), Hu and Yasuda (2006) and Yasuda *et al.* (2005) introduced GGA method with new modified crossover, mutation operators, correction scheme and a new codification scheme of chromosomes based on machine groups rather than individual machine. The proposed methodology efficiently converges with lesser CPU time irrespective of number of parts. While Vin *et al.* (2005) introduced the MOGGA technique combined with CF heuristic by considering process sequence, production volume and alternative routing. Further, James *et al.* (2007) extended GGA as a hybrid technique combined with local search which outperformed well-known techniques including conventional GGA. On the other hand Tunnukij and Hicks (2009) presented an improved EnGGA method by employing a new approach called rank-based roulette–elitist strategy, for creating successive generations. Onwubolu and Mutingi (2001) addressed multi-objective GA with three objective functions: minimization of intercell moves, cell load variation and the combination of both the former objectives, the technique further competed with hybrid GA and TS methods with improved computational result. Chi and Lin (2002) proposed new technique called EOG which is a mixed form of granular computing and GA, to enhance the simplicity of computation, and its ability to handle large-size problem. Mansouri *et al.* (2003) considered the chromosome of MOGA as a vector of many decision variables and the fitness function is a function of multiple sub-objective functions. Whereas Solimanpur *et al.* (2004) introduced multiple fitness function which generates several solutions along the pareto-optimal frontier; hence the proposed MOGA yielded decision support system for CFP. Goncalves and Resende (2004) stated that GA could be more effective with local heuristics in solving CFP. Tavakkoli-Moghaddam *et al.* (2005) proposed TS, SA and GA methods separately to solve dynamic CFP and reported that SA is better in terms of solution and complexity than the TS and GA. Rogers and Kulkarni (2005) introduce bivariate clustering of matrix for CFP and a GA based method was employed to solve the problem with improved result. Rajagopalan and Fonseca (2005, 2006) proposed a VSM with production volume limit for individual component rather than using product mix and implemented a new GA-model to show that volume limit could enhance the choice of optimal routing of components when machine movement is not viable and the authors further published their GA-model to reduce intercellular and intracellular material handling cost with other cost components such as backtracking cost, machine skipping cost and penalty cost subsequently.

Nsakanda *et al.* (2006) modelled a GA method combined with price-directed decomposition method for large-scale MOCFP. Boulif and Atif (2006, 2008) stated a graph partitioning formulation of CFP which utilized a binary GA and then a B&B method to enhance the GA and in another study the authors further considered dynamic production factors such as input data with realistic constraints and avoided assumptions such as static number of cells, hence they proposed an improved GA based methodology with the help of fuzzy logic. Chan *et al.* (2006) considered two mathematical models, one is a CFP to minimize intracell and intercell part movement, and other is a CLP to minimize intercell part travelling distance. Defersha and Chen (2006, 2008a, 2008b) developed a mathematical model which incorporated dynamic cell configuration, alternative routings, sequence of operations, multiple units of identical machines, machine capacity, workload balancing among cells, operation cost, subcontracting cost, tool consumption cost, set-up cost and other practical constraints and a two-phase GA-based-heuristic technique was proposed. The authors further experimented with parallel GA model for dynamic-CFP considering various parameters such as connection topology, migration policy, migration frequency and migration rate. In another article the authors attempted to minimize production and quality related costs by incorporating a number of manufacturing attributes and practical constraints by considering multi-item and multi-level lot sizing aspects and the impact of lot size on product quality. Wu *et al.* (2006) introduced a hierarchical GA method to solve CF problem and also a group layout problem with 2-20% improvement in result. Car and Mikac (2006) proposed a method based on Emergent Synthesis idea which is utilized in MGA. Ponnambalam *et al.* (2007) developed a modified grouping efficiency and proposed a GA technique which outperformed traditional techniques such as K-mean clustering and ART1 algorithms. Whereas GA based robust design methodology practiced by Pillai and Subbarao (2007) to forecast the product mix and demand changes during periods of a planning horizon without allowing the composition of machine cells to change over time. Mahapatra and Pandian (2008) considered the operational time and sequence of operation of parts, to minimize cell load variation and EEs. The implemented GA method outperformed K-mean clustering and C-link clustering algorithms.

Besides, Ming and Ponnambalam (2008) proposed a GA-PSO approach and the methodology successfully applied to minimize total cell load variation and total components move. Chan *et al.* (2008) introduced CFP with IAECLP to minimize total part movements and total sum of intracell and intercell part distances due to machine sequence and sequences of newly formed cells. However Tariq *et al.* (2009) developed a local search heuristic based on GA which yielded best solution ever found in literature. Cao *et al.* (2009) formulated a mathematical model for optimal lot splitting into alternative routes to account for either positive or negative effects of production run length on product quality in CM environment. Kor *et al.* (2009) aimed to implement SPEA-II and compared with GP-SLCA to produce improved result. Fan *et al.* (2010) discussed the dual resource-constrained system model for CFP by considering minimum distance of parts and also employees move among cells, the number of hired employees and the load balance of staff. Pailla *et al.* (2010) proposed two methodologies for CFP, one is a modified-EA based on genetic operator-heuristic and second is based on simulated annealing which outperformed the EA. Neto and Filho (2010) designed a multi-objective-optimization model using GA, where fitness evaluation was performed via simulation of CM. while Deljoo *et al.* (2010) worked on dynamic production condition considering product mix, demand of parts during some period, machine movement, addition of new equipment, by providing flexibility in CM.

The abovementioned survey is majorly focused on cell formation attributes selected in CMS, therefore, to incorporate the detailed simulation results obtained from the reviewed GA based techniques, Table 1a to 1d are presented.

Table 1a. Simulation results obtained from reviewed techniques

References	*Initial Population*	*Fitness function*	*Selection strategy*	*Stopping Criteria*
Venugopal and Narendran (1992)	randomly generate the initial population	Total intercell moves and within cell load variation	*stochastic remainder selection* without *replacement* scheme	Fixed no. of iteration
Gupta *et al.* (1996)	randomly generate the initial population	Objective function taken	*stochastic remainder selection* without *replacement* scheme	Fixed no. of iteration
Joines *et al.* (1996)	Random seeding	Nonlinear form of grouping efficacy	Normalized geometric ranking scheme	maximum number of generations
Morad and Zalzala (1996)	initial population is generated at random	Objective function taken	elitist strategy	maximum number of generations
Hwang and Sun (1996)	permutations generated with the numbers	Scaled fitness sf_{ji} = *fitness + offset /(sum (fitness/PS +offset)*	stochastic remainder sampling without replacement	maximum number of generations
Zhao *et al.* (1996)	randomly generated by heuristic	rank - based evaluation function	roulette wheel approach	maximum number of generations
Kazerooni *et al.* (1997)	randomly generated	number of elements in the MCS matrix which have a value equal to zero or below L_n	tournament strategy	maximum number of generations
Al-Sultan and Fedjki (1997)	random generation	objective function value	biased roulette wheel approach	maximum number of generations
Pierreval and Plaquin (1998)	randomly generating algorithm	total cost or the homogeneity of the workload distribution on each cells	niched pareto tournament selection	If all the machines are placed in cell
Gravel *et al.* (1998)	generated randomly	objective function value	chosen by fitness	When the diversity drops to zero or loss of diversity of the machine cell population should not exceed 3%.
Hsu and Su (1998)	generated randomly	total cost, and total machine loading imbalances	chosen by fitness	maximum number of generations
Moon and Gen (1999)	generated randomly	objective function value	Deterministic selection strategy	maximum number of generations
Zhao and Wu (2000)	generated randomly	objective function value	chosen by fitness	maximum number of generations
Mak and Wong (2000)	Generate an initial population of individuals randomly	objective function values	chosen by fitness	maximum number of generations
Mak *et al.* (2000)	Randomly generated	Bond energy measure	traditional roulette wheel selection operator	maximum number of generations
Lee-Post (2000)	Generate randomly	sum of similarities	selected probabilistically	time-bounded rule & quality-bounded rule
Plaquin and Pierreval (2000)	generated randomly	inter-cell traffic function	Based on aggregates and their belongingness	When there is no aggregate left to place
Onwubolu and Mutingi (2001)	randomly created solution space	Cost function	remainder stochastic sampling without replacement	maximum number of generations

Table 1b. Simulation results obtained from reviewed techniques

References	***Initial Population***	***Fitness function***	***Selection strategy***	***Stopping Criteria***
Chu and Tsai (2001)	variable restriction method **to** generate randomly	minimizing the number of EEs	roulette wheel selection method	number of generations
Brown and Sumichrast (2001)	Random generation	Based on objectives	rank-based roulette-wheel selection	number of generations
Chi and Lin (2002)	initial radius of the hyperboxes	Objectives and grouping efficiency	stochastic sampling method without replacement	Fixed no. of iteration
Wu *et al.* (2002)	randomly generate the initial population	Total number of EEs	roulette wheel approach	maximum number of generations
Zolfagharia and Liang (2003)	randomly generated	generalized grouping efficacy	random selection, roulette wheel selection, stochastic universal sampling	maximum number of generations
Mansouri *et al.* (2003)	Randomly Generate Initial Solutions	Based on normalize factor and objective value	*Reminder Stochastic Sampling Without Replacement* in conjunction with a new Elitism operator	either it converges to a robust non-dominated frontier or a predetermined number of generations
Chan *et al.* (2004)	random population	Based on objective function	Individuals with higher fitness value	variation in the value of the best objective function

Table 1b. (cont'd) Simulation results obtained from reviewed techniques

References	*Initial Population*	*Fitness function*	*Selection strategy*	*Stopping Criteria*
Chi and Yan (2004)	generated randomly	Fuzzy objective function	roulette wheel approach	maximum number of generations
Goncalves and Resende (2004)	randomly generated	objective function	elitist strategy	Maximum No. of generation
Solimanpur *et al.* (2004)	randomly generated	Total objective function	Probabilistic selection	Maximum No. of generation
Zolfaghari and Liang (2004)	randomly generated	Based on objectives	Best fit parents selected randomly	Maximum No. of generation
Pai *et al.* (2005)	generated randomly	grouping efficacy	roulette wheel selection principle	maximum number of generations
Vin *et al.* (2005)	Generate an initial population using a resource planning (RP) heuristic	Cost function	Individuals with higher fitness value	maximum number of generation without improvement
Rogers and Kulkarni (2005)	randomly generated	objective function + penalty function	standard proportional selection incorporating the elitist model	Maximum No. of generation
Rajagopalan and Fonseca (2005)	randomly generated	Production volume function considering upper limit and lower limit of VSM	tournament selection	Maximum No. of generation considering upper limit and lower limit of VSM
Hu and Yasuda (2005)	Random heuristic	Fitness=-A1×C×f1-A2/C×f2	probabilistic selection	Maximum No. of generation
Rajagopalan and Fonseca (2006)	randomly generated	material handling cost + penalty cost	tournament selection	a run of 5000 generation
Filho and Tiberti (2006)	special procedure based on random generation	Sum of the objectives	Roulette Wheel selection procedure	Maximum No. of generation
Nsakanda *et al.* (2006)	randomly generated using population diversity	Total move cost + total outsourcing cost	stochastic remainder selection without replacement method	No. of generation, number of chromosomes evaluations exceeds, improvement in fitness value, population diversity drops

Table 1c. Simulation results obtained from reviewed techniques

References	*Initial Population*	*Fitness function*	*Selection strategy*	*Stopping Criteria*
Boulif and Atif (2006)	randomly generated initial population	objective function	Roulette wheel random procedure	Maximum No. of generation
Chan *et al.* (2006)	Initially generated randomly	Based on objective function	Chromosomes with higher fitness value	little change of improvement in the best objective function
Defersha and Chen (2006)	Random generation	Sum of the objectives	biased roulette wheel approach	Maximum No. of generation
Wu *et al.* (2006)	randomly generated	Based on objective function	roulette wheel and elitist approach	Maximum No. of generation
Car and Mikac (2006)	random selection of individuals	sum of total number of voids and the total number of EEs	Individuals with higher fitness value	Maximum No. of generation
Ponnambalam *et al.* (2007)	generated randomly	objective function	maximum fitness function value	Maximum No. of generation
Pillai and Subbarao (2007)	randomly created population	objective function	Best fit chromosomes	Maximum No. of generation
James et al. (2007)	Random generation	Based on rank and no. of ranked chromosomes	Rank-based roulette wheel selection	No. of generation
Tavakkoli-Moghaddam *et al.* (2007)	greedy generational handling strategy	objective function + penalty function	roulette wheel sampling	Maximum CPU time, standard deviation of generation,
Boulif and Atif (2008)	Random generation	objective function	roulette wheel approach	Maximum No. of generation
Chan *et al.* (2008)	Random population	objective function	Best fit chromosomes	little change in the best objective function
Defersha & Chen (2008a)	Random generation	Sum of the objectives	biased roulette wheel approach	No. of generation, improvement in fitness value
Defersha & Chen (2008b)	Random generation	Sum of the objectives	biased roulette wheel with replacement	improvement in fitness value
Mahapatra & Pandian (2008)	Generate random population	objective function	Random selection	Maximum No. of generations
Mahdavi *et al.* (2009)	special procedure was developed	total number of voids and EEs	Roulette Wheel selection procedure	Maximum No. of generations
Tariq *et al.* (2009)	Random generation	objective function	Best fit chromosomes & roulette wheel approach	improvement in fitness value
Tunnukij and Hicks (2009)	Random generation	Grouping efficacy	Random selection & Rank-based Roulette-elitist Strategy	Maximum Number of generation

Table 1c. (cont'd) Simulation results obtained from reviewed techniques

References	*Initial Population*	*Fitness function*	*Selection strategy*	*Stopping Criteria*
Kor *et al.* (2009)	Random generation	closeness to the true Pareto front and even distribution of solutions	Binary tournament selection with replacement	Maximum No. of generations
Cao *et al.* (2009)	Random generation	Objective function value	Best fit chromosomes	No. of generation, improvement in fitness value
Neto & Filho (2010)	first half is generated by using problem-specific information & second half is generated randomly	Feasibility correction is used to check objective value therefore fitness	NSGA-2 built-in ''crowding" tournament used	Maximum No. of generation

Table 1d. Simulation results obtained from reviewed techniques

References	*Initial Population*	*Fitness function*	*Selection strategy*	*Stopping Criteria*
Pailla et al. (2010)	Random Generation & constructive heuristic used	grouping efficacy	Selection probability function used from Joins et al. (1996)	Maximum No. of generation
Fan *et al.* (2010)	Random generation	Objective function of CFP used	Roulette wheel method	Maximum No. of generation
Deljoo *et al.* (2010)	Sequential strategy used	Objective function of CFP used	Best fit chromosomes taken & normalized method used	No. of generation, upper bound of solving time, improvement in fitness value

4. Discussion

Present section prefaces a thorough analysis of the GA methods and remonstrate some delicate issues based on the discussion of previous section. This work compensates comprehensive amount of research papers based on genetic cell arrangement in CMS, therefore a large sphere of CMS is covered which not only includes CFP but also considers plant layout area and several multi-objective issues and performance metrics. Papers are categorized on the basis of several GA based techniques. To improve this discussion, this section is divided into following sub-sections,

4.1 Multi-objective evolutionary cell formation: In general CFPs are articulated in more complicated way by means of multiple objectives, such as intercell or intracell part movements, within cell load variation, count of EEs and voids, machine utilization, machine investment, machine duplicacy, WIP level, part subcontracting, part cycle time, part routing, operational time, operational sequence of parts. Table 2 classifies literatures based on multi-objective CFP model as reported by Ghosh *et al.* (2010).

Table 2. List of papers with multi-objective CFPs

References	**Obj1**	**Obj2**	**Obj3**	**Obj4**	**Obj5**	**Obj6**	**Obj7**	**Obj8**	**Obj9**
Neto and Filho (2010)	✓	✓	✓						
Vin *et al.* (2005)		✓				✓			✓
Zhao and Wu (2000)		✓		✓	✓				
Brown and Sumichrast (2001)		✓				✓			
Gupta *et al.* (1996)		✓		✓					
Hsu and Su (1998)		✓	✓	✓					
Mansouri *et al.* (2003)		✓					✓	✓	
Solimanpur *et al.* (2004)			✓						✓
Yasuda *et al.* (2005)		✓		✓					
Wu *et al.* (2006)		✓			✓				
Dimopoulos (2006)		✓				✓			
Tavakkoli-Moghaddam *et al.* (2007)		✓	✓						
Defersha and Chen *et al.* (2008)		✓	✓						
Goncalves and Resende (2004)		✓				✓			
Gravel *et al.* (1998)		✓		✓					
Chi and Yan (2004)		✓		✓					
Fan *et al.* (2010)		✓		✓					

Table 2. **(cont'd)** List of papers with multi-objective CFPs

References	Obj1	Obj2	Obj3	Obj4	Obj5	Obj6	Obj7	Obj8	Obj9
Morad and Zalzala (1996)		✓		✓					
Kor *et al.* (2009)		✓		✓					
Mahapatra and Pandian (2008)				✓	✓				
Mak and Wong (2000)		✓		✓					
James *et al.* (2007)		✓				✓			
Pierreval and Plaquin (1998)		✓		✓					
Tariq *et al.* (2009)		✓				✓			
Ming and Ponnambalam (2008)		✓		✓					
Solimanpur *et al.* (2010)	✓	✓						✓	

- *Obj1: Level of WIP*
- *Obj2: intercell and/or intercell move*
- *Obj3: Machine investment/modification/relocation*
- *Obj4: Cell load variation*
- *Obj5: Count of EEs and/or Voids/Operational sequence/time*
- *Obj6: machine utilization/cycle time of parts*
- *Obj7: machine duplication & part subcontracting*
- *Obj8: system under-utilization/ cells utilization/system reliability*
- *Obj9: part processing/routing/time/cost/total work content of parts*

From Table 2 few points can be concluded,

- Around 40% of the papers cover more than two objectives.
- Around 30% of the papers include common objectives such as minimizing intercell or intracell material handling cost, cell load variation and maximizing machine utilization.
- Other objectives considered are, level of WIP, machine investment/ modification/ relocation cost, parts cycle time/part processing/ routing, total work content of parts, machine duplication, part subcontracting, system under-utilization, cell utilization and system reliability.
- Around 50% of total papers reviewed in this article, are dedicated to handle multi-objective issues.
- In order to consider multi-objective CFPs, multi-objective GAs are required. Therefore various complex multi-objective GAs are employed such as NSGA, SPEA, NPEA, MOGA and MOGGA which are known as established techniques for engineering optimization problems.

3.2 Comparison of different GA based methodologies: In this sub-section a comparative analysis is performed on different CFP formulations. Table 3 indicates the list of references, the corresponding methodology used, and the corresponding platform on which the methodologies are tested and table 4a and 4b shows the numbered references and various issues such as, the published data taken with which the present methodology experimented or the established method with which the proposed technique is compared, the execution time of the technique, improvement from published result (in percentage) and selected parameters of the evolutionary method (generation number, population size, crossover rate, mutation rate), while the last column presents few comments about the corresponding study.

Table 3. List of references opted for comparison of GA techniques in CFP

No.	*References*	*Techniques*	*System Specifications*
1	Neto and Filho (2010)	NSGA 2	P4 HT 3 GHz and 1 GB of RAM.
2	Zhao and Wu (2000)	MOGA	Pentium/100MHz
3	Anita Lee-Post (2000)	GA-DCLASS	sun sparc station 1+
4	Dimopoulos and Mort (2001)	GP-SLCA	
5	Brown and Sumichrast (2001)	GGA	
6	Gupta et al. (1996)	GA-ANOVA	TURBO PASCAL IBM PS/2 55SX
7	Hsu and Su (1998)	modified GA	
8	Mansouri *et al*. (2003)	XGA	PII (Celeron) 333MHz 64MB RAM
9	Solimanpur *et al*. (2004)	MOGA	
10	Chan *et al*. (2004)	Simple GA	

Table 3. **(cont'd)** List of references opted for comparison of GA techniques in CFP

No.	***References***	***Techniques***	***System Specifications***
11	Yasuda *et al*. (2005)	GGA	Intel P3, 1 GHz CPU. 256MB RAM
12	Rajagopalan and Fonseca (2005)	GAM	
13	Al-Sultan and Fedjki (1997)	modified GA	
14	Hu and Yasuda (2005)	GGA	Intel P3 1 GHz processor, 256MB RAM
15	Dimopoulos (2006)	MO GP-SLCA-NSGA 2	
16	Tavakkoli-Moghaddam *et al*. (2007)	GA heuristic	Celeron Mobile 1.3 GHz 512 MB RAM
17	Chan *et al*. (2008)	simple GA	
18	Defersha and Chen (2008)	island model PGA	P4 processor (3.2 GHz, 2GB RAM)
19	Goncalves and Resende (2004)	GA & LSH	AMD Thunderbird 1.333 GHz processor
20	Boulif and Atif (2006)	GA & B&B	Cyrix MII 300/ 233MHz and 32 MB RAM
21	Rogers and Kulkarni (2005)	simple GA	P3 700 MHz workstation 256 MB RAM
22	Gravel *et al*. (1998)	double loop GA	Intel Pentium Pro 200 MHz
23	Tunnukij and Hicks (2009)	EnGGA	laptop with a 1.66GHz processor
24	Pai *et al*. (2005)	fuzzy GA	PIII750 CPU and 192M RAM
25	Zhao *et al*. (1996)	fuzzy GA	
26	Onwubolu and Mutingi (2001)	modified GA	Pentium/133MHz processor
27	Cao *et al*. (2009)	GA-simplex heuristic	Pentium IV (2.93 GHz, 512MB RAM)
28	Morad and Zalzala (1996)	simple GA	
29	Kor *et al*. (2009)	GA-SPEA 2	
30	Ponnambalam *et al*. (2007)	simple GA	Pentium IV machine
31	Mahapatra and Pandian (2008)	GA heuristic	Pentium IV PC, 2.4 GHz processor
32	Mak and Wong (2000)	GA-ANOVA	Pentium 200–based PC
33	Chu and Chang-Chun-Tsai (2001)	GA with heuristic	Pentium I11 processor and 96 MB of RAM
34	Wu *et al*. (2002)	hierarchical GA	Pentium IV (1300 MHz) processor
35	James *et al*. (2007)	GGA with local search heuristic	2.00 GHz processor personal computer
36	Nsakanda *et al*. (2006)	GA, large scale optimization technique	IBM RISC 6000 model 3BT
37	Tariq *et al*. (2009)	GA-LSH	
38	Car and Mikac (2006)	modified GA	IBM compatible Pentium computer
39	Vin *et al*. (2005)	MO GGA	786 MB RAM 450 MHz computer
40	Pillai and Subbarao (2007)	simple GA	
41	Pierreval and Plaquin (1998)	NPEA	workstation HP 9000 Series 710
42	Pailla *et al*. (2010)	hybrid EA-LSH	1.410 GHz AMD Athlon microcomputer
43	Tavakkoli-Moghaddam *et al*. (2005)	GA heuristic	Pentium IV 2.1 GHz computer
44	Plaquin and Pierreval (2000)	EA	HP 9000 Series 710
45	Wu *et al*. (2007)	simple GA	Intel Pentium IV (1300 MHz)
46	Filho and Tiberti (2006)	modified GGA	
47	Mahdavi *et al*. (2009)	GA heuristic	p4, 2.1 GHz with 512 Mb of RAM
48	Hwang and Sun (1996)	GA & greedy heuristic	IBM PC 486
49	Deljoo *et al*. (2010)	GA heuristic	Pentium IV 3 GHz AMD and 512 MB RAM

Table 4a. Comparison of GA techniques in CFP

No.	***Compared/ Experimented with***	***Run time***	***Improvement***	***GN***	***PS***	***Pc***	***Pm***	***Comment***
1	Wu (1998)	8 hrs.	33%	50	50	1	0.5	MO Stochastic Programming model taken
2	Boctor (1991)	2 min	14%					dynamic programming based mathematical model
3	industrial data	2 sec	33%					similarity coefficient technique used
4	ZODIAC GRAFICS MST-GRAPHICS		better or equal	50	500	0.9	0.1	similarity coefficient used/ grouping efficacy tested

Table 4a. **(cont'd)** Comparison of GA techniques in CFP

No.	*Compared/ Experimented with*	*Run time*	*Improvement*	*GN*	*PS*	*Pc*	*Pm*	*Comment*
5	ZODIAC	21 generation	17%	21	50/ 100/ 200	1/ 0.6	0/0.25	grouping efficiency used as performance measure
6	Logendran (1990, 1991)		better	10/20/40	10/20/40	0.1/0.6/0.9	0.05/0.1/ 0.15	objective taken as to minimize total moves
7	Logendran (1991), Gupta *et al*. (1996)		better					multi criteria MP model proposed
8	NSGA		22.20%		150	0.5	0.03	MO optimization problem model used and XGA is 31.7% faster than NSGA.
9	Gupta *et al*. (1996), Akturk and Turcan (2000)		better	700	50		0.1	MO Integer programming model suggested
10	joins *et al*. (1996)		better		200	0.8	0.001	MP model used
11	Venugopal and Narendran (1992), ZODIAC	197.6, 919.2 sec	6-17%	11,27	40	0.9	0.3,0.4	MO MP model
12	Verma and Ding (1995)		4-9%	100; 5000	20,50	0.8	0.01, 0.001	Volume Sensitivity Model used
13	Hon and Chi (1998), Burbidge (1975), Dewitte (1980)	27-824 sec	36%					integer quadratic programming model used
14	Sofianopoulou (1999)	363 sec	better		40/80/60	0.8/0.9	0.4	part processing route & operation sequence considered
15	Gupta *et al*. (1996)		competitive	1000	50	0.5	0.5	MO MP model proposed
16	B&B solution, LINGO		2.291% gap	10000	200/300	0.8	0.18	fuzzy non-linear mixed integer programming model used
17	Joines (1993), Kazerooni *et al*. (1997)		better		300	0.9	0.001	MOCFP-IAECLP
18	LINGO, SGA	3600 sec	better					integer programming model taken
19	Carrie (1973)	43.78 sec	11%					grouping efficacy measure utilized
20	binary coded GA	305.54 sec	2.28%	2000/3000	250	0.8	0.01	objective is to reduce intercell traffic
21	Burbidge (1969) and Lee *et al*. (1997)	2 h/5 h	11-20%	5000		0.87	0.001	mixed integer LP model, bivariate clustering used
22	random data		near efficient					parts with multiple routing taken into account
23	McCormick *et al*. (1972)	<40 sec	7.14%	50	100/1000	>=0.6	<=0.4	grouping efficacy measure utilized
24	Balakrishnan and Jog (1995)	42 sec	7.70%	400				grouping efficacy measure utilized
25	Chu and Hayya (1991)	520 sec	11.50%	2000	50	0.7	0.1	non-linear integer programming model taken into account
26	Chan and Milner (1982)		92%					MO math model used, clustering efficiency checked
27	industrial data		optimal solution					mixed integer non-linear programming model considered
28	Burbidge (1963)		better		40	0.7	0.05	multi criteria MP model proposed/similarity coefficient technique adopted

Table 4b. Comparison of GA techniques in CFP

No.	*Compared/ Experimented with*	*Run time*	*Improvement*	*GN*	*PS*	*Pc*	*Pm*	*Comment*
29	Dimopoulos and mort (2001)		39%					multi objective MP model
30	Yiu-Ming Cheung (2003), Mahapatra *et al*. (2006)		38.70%	250	10	0.7	0.1	modified grouping efficiency measure utilized

Table 4b. (cont'd) Comparison of GA techniques in CFP

31	V&N (1992), Prabhakaran *et al*. (2002)	3.62637 sec	16%	100-900	15-25	0.5	0.1	modified grouping efficiency measure utilized
32	Srinivasan *et al*. (1990), Chan and Milner (1982)	2 min	15.40%	100	40	0.8	0.01	Grouping efficacy measure used
33	LINDO, GA	84.1 sec	27.70%		10-100			Grouping efficacy measure used
34	Chandrasekharan and Rajagopalan (1993)	24 sec	19%		100	0.95	0.3	cost of total moves reduced
35	brown and Sumichrast (2001)	0.43-2.3 sec	91.42%	50	100			average solution quality compared
36	open literature		better or equal	1000	10–50	0.6		objective is to minimize intercell move cost
37	open literature		41.67%					Grouping efficiency measure used
38	ROC, ART1		50%		60	0.5	0.5	Grouping efficacy measure used
39	(Vivekananda and Narendran 1998), (Askin, 1997)	10-75 sec	better					Machine utilization is considered in comparison
40	Wicks and Reasor (1999)		14.42%	100	80-250	0.8	0.1	total moves & machine acquisition cost minimized
41	industrial data	30 min	competitive		100	0.6	0.4	intercell traffic & cell workload minimized
42	Goncalves and Resende (2004); Joines *et al*. (1996)	0-80 sec	33%	150				compare SA & GA
43		0-5250 sec	competitive	100/150/200	100/150/200			compared with SA & TS
44	random workshop data		competitive		100	0,2		objective is to minimize intercell traffic
45	Chandrasekharan and Rajagopalan (1993)		competitive	100 /200	50/ 100	0.7 /1.0	0.1 /0.5	reduced intercell traffic & no.of EE, ANOVA used to understand effect of parameters of GA
46	Zolfaghari and Liang (1997), V&N (1992).		competitive	Variable	20–40	0.80–0.90	0.01–0.1	cell layout design performed & group structure found from data set
47	C&R (1989), Stanfel (1985), King (1980)	0-100 sec	27.30%	Variable	50–200	0.70–0.80	0.01–0.1	Grouping efficacy measure used
48	INCFR & NLCA	2.3-241.6 sec	97%	30	30	0.8	0.05	group efficiency measure verified
49	random data	<9 min	better					global optimum value compared with LINGO

The conclusion drawn from Table 3, 4a and 4b are,

- Most of the GA techniques are tested on powerful computers due to their high processor speed and higher memory, which can eventually reduce the computational time of the genetic operations which further implies low computer resource investment.
- GA is employed with hybridization or substantial modification due to the growing complexities of cellular manufacturing systems.
- Efficiency is tested on some common test data taken from Venugopal and Narendran (1992), Chandrasekharan and Rajagopalan (1987), Gupta *et al*. (1996), Burbidge (1963), and most popular techniques are ZODIAC, GRAFICS and MST with which the implemented algorithms are compared frequently.
- Around 50% of the papers convey information about computational time of the algorithm to perform the experiments.
- Around 60% of the papers report numerical figure of improvement rather than proposing this in qualitative term. Measures for the improvement usually not identical for every work, and these oscillate among grouping efficacy, grouping efficiency, modified measures, or the efficiency in terms of machine utilization, reduction in EE count, total cell moves, followed by other metric system which can perform comparison among techniques.
- The general trend of selection range of GA parameters are, Generation No. 50-500, Population size 50-200, crossover rates 0.5-0.9, mutation rates 0.01-0.1 and with these parameter values GA is capable to produce good solutions.
- Despite of the fact that proposed multi-objective models are capable of producing good result but due to lack of realistic industrial data set these techniques are not fully utilized in solving CFPs (Dimopoulos, 2006).

- “Figure 2” depicts performance improvement of GA methods obtained from table 4a and 4b when compared with some previously published results. 5-6% of papers report improvement result by more than 50% whereas others present moderate enhancement while obtaining solutions.

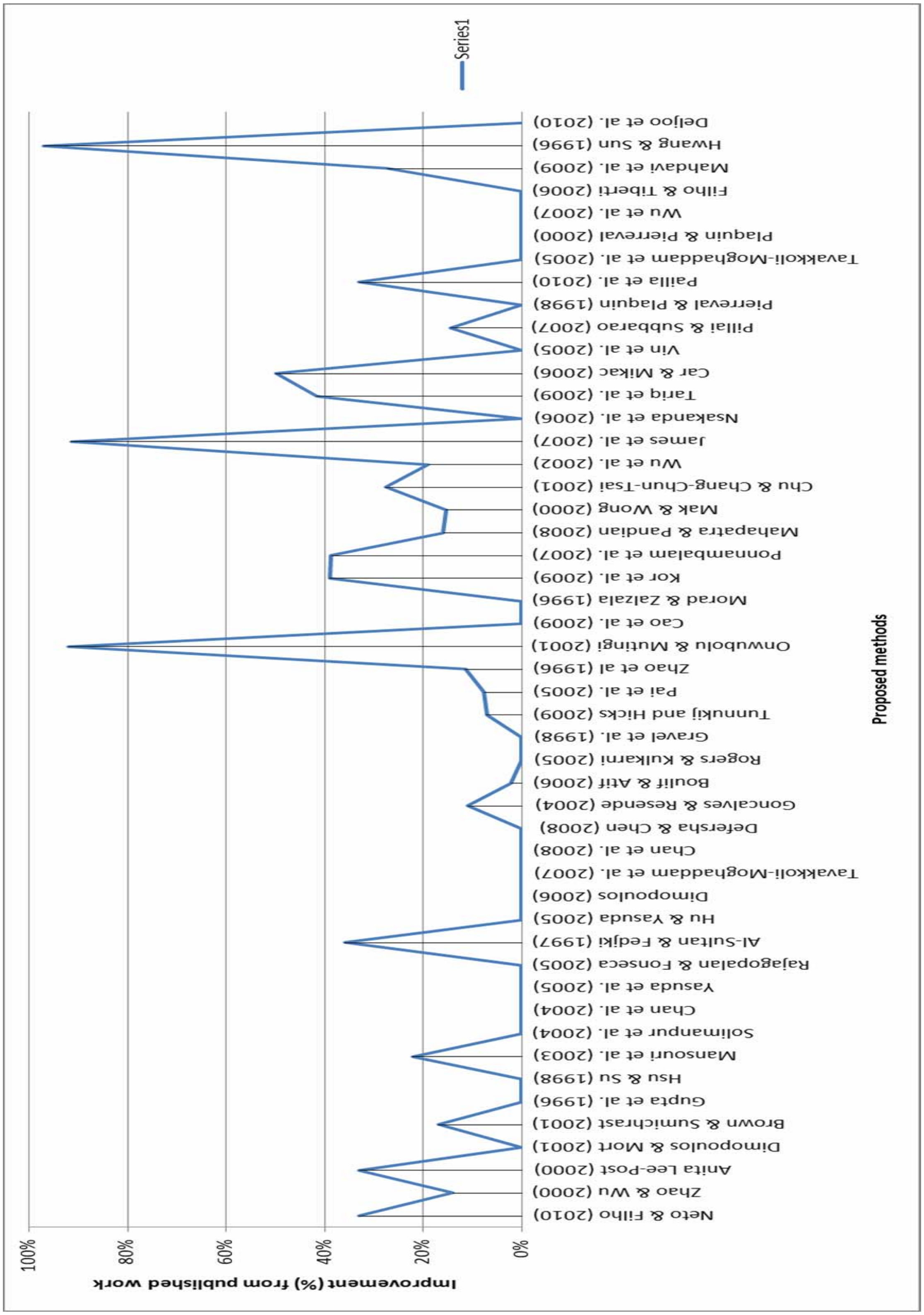

Figure 2. Percentage improvement curve showing the superiority of proposed techniques of literature over published result

4.3 Use of hybrid genetic techniques: Only few papers are focused on hybrid techniques based on various GA with other metaheuristics, exact methods or other heuristic techniques in CFP area. This is also an emerging research area where new methods based on hybrid GA can be formed and utilized further. Table 5 shows the number of papers available in CFP which demonstrate the possibility, effectiveness and usability of such hybrid techniques. The two different forms of hybridization are demonstrated from literature (Bianchi *et al.*, 2009), such as, (1) Component Exchange Method, (2) Cooperative Search method.

- *Component Exchange Method*: It performs inclusion of components of one algorithm into another. The basic idea behind this is, population-based methods are efficient in identifying promising area in search space and deterministic or single solution based methods are good in exploring the promising area, hence hybridisation is required.
- *Cooperative Search method*: It brings parallelism in techniques execution with different level of communication. It is possible for different algorithms to exchange information about states, models, solutions, sub-problems and different attributes of search space among each other.

While comparing with recent review work proposed by Papaioannou and Wilson (2010), this article presents more intricate study of GA based techniques as a solution methodology in cellular manufacturing. The nobility of this paper is to put prime concentration in genetic approaches and a detailed discussion based upon many critical issues as stated above.

From the study presented in this article, followings are summarized,

a. GA is established methods in engineering optimization problem, reflection is found in CF domain as well. Mid 90s onwards GA is proposed to be a stand-alone tool and also as a hybrid technique and being used rigorously till present time in search of better solutions.
b. In early stages single objective CFP was of researchers' prime interest, but in later stage since manufacturing decisions are becoming more complex, therefore multi-objective CFPs are considered frequently by focusing on operational time, sequence, alternative process routing, machine duplicacy, dynamic conditions, and several costs related to CMS.
c. Multi-objective GA methods such as NPEA, NSGA, MOGA, MOGGA are being adopted to solve such multi-objective CFPs.
d. Due to large problem size, computational time is major concern of many researchers, and hence improved evolutionary optimization techniques are being proposed accordingly.
e. Powerful computer systems are required to execute such techniques.
f. Large size industrial data is required to test the efficiency of such complex techniques.
g. In case of hybridization, although the component exchange method is used frequently but cooperative search method is yet to be fully utilized.
h. Enhancement is reported in terms of efficacy of proposed technique as well as the computational time. Hence enhancement could be identified while experimental technique produces identical result to the published result with consumption of low computer resources.

Table 5. Papers with hybrid genetic algorithm methods

Reference	***Technique***	***Tool used***
Ming and Ponnambalam (2008)	GA-PSO	**
Boulif and Atif (2006)	GA-B&B	Borland C++
Zhao et al (1996)	GA-fuzzy	**
Chi and Yan (2004)	GA-fuzzy	**
Tunnukij and Hicks (2009)	GGA-GH-RES	C
Chu and Chang-Chun-Tsai (2001)	GA, heuristic	C
Nsakanda et al. (2006)	GA-LSOT	C
Cao et al. (2009)	GA-simplex LP	C++
James et al. (2007)	GGA-LSH	VB .NET
Defersha and Chen (2008b)	GA-LP	C++
Pai et al. (2005)	GA-fuzzy	**
Goncalves and Resende (2004)	GA-LSH	VO 2.0b-1
Tariq et al. (2009)	GA-LSH	**
Hwang and Sun (1996)	GA-GH	**

*** Data not available*

5. Conclusion

This paper postulates a detailed review of recent CF based genetic techniques. Since mid-90s GA has evolved as a powerful optimization technique in CFP and a substantial amount of research papers are reported which employed these techniques. A comprehensive list of papers is recognized which proposed multi-objective GA model, and these techniques are dominating as a solution methodology in Cellular Manufacturing over the last two decades. Since substantial research works are already performed with simple GA in single objective CFP domain, therefore research trend is observed in implementing modified GA methods, which are capable to outperform simple GA in many instances and this article reflects a clear trend of using these population based modified methodologies as collateral techniques of GA to solve multi-objective CFP. Subsequently research papers are classified based on various issues of GA such as its parameter selection, computer resource usage, hybridization and enhancement from past work, which finally identify future research scope in this narrow area. The research direction of Selim *et al*. (1998) and Papaioannou and Wilson (2010) are thus partially accomplished. Ghosh *et al*. (2010) proposed the trend towards the adoption of the metaheuristics approaches in CFP domain, but due to absence of complex industrial data set, competency of GA based metaheuristic techniques were not fully practiced (Dimopoulos, 2006). It can be stated from this study that new techniques are being employed along with GA as hybrid techniques due to the growing complexities of industrial problems. The forthcoming research should complement its flaws, thus creating powerful approaches to solve realistic GT/CM problems. The major verdict of this research work is to identify the trend of GA in CMS, which was started with very basic simple genetic algorithm in 1990 and gradually evolved with such complex hybrid techniques in recent time. For example, GA-SS, EP-heuristic, SS-PSO, DE-ACO, SA-GP, TS-MA and other similar approaches would be spot-on to solve large scale optimization problems in aforesaid domain with precise focus on reduced computational time and enhanced efficiency.

Nomenclature

GT: Group Technology.
CM: Cellular Manufacturing.
CMS: Cellular Manufacturing System.
CF/CFP: Cell Formation Problem.
TS: Tabu Search.
EA: Evolutionary Algorithm.
ACO: Ant Colon Optimization.
PSO: Particle Swarm Optimization.
SA: Simulated Annealing.
GA: Genetic Algorithm.
EEs: Exceptional Elements.
LP: Linear Programming.
EP: Evolutionary Programming.
GP: Genetic Programming.
DE: Differential Evolution.
SS: Scatter Search.
MA: Memetic Algorithm.
WIP: Work in Process.
C&R: Chandrasekharan and Rajagopalan.
V&N: Venugopal and Narendran.
B&B: branch & bound.
LSH: local search heuristic.
MO: multi-objective.
NPEA: niched Pareto evolutionary algorithm.
GAM: GA model.
ANOVA: Analysis of Variance.
MOGGA: Multi-Objective Grouping Genetic Algorithm.
VSM: Volume Sensitivity Model.
MGA: Modified Genetic Algorithm.
ART: Adaptive Resonance Theory.
NSGA II: Non-Dominated Sorting Genetic Algorithm II.
IAECLP: Intra-cell And Inter-Cell Layout Problem.
EnGGA: Enhanced Grouping Genetic Algorithm.
SPEA: Strength Pareto Evolutionary Algorithm.
PGA: Parallel Genetic Algorithm.
GGA: Grouping Genetic Algorithm.
SLCA: Single Linkage Clustering Algorithm.
GMPG: General Machine-Part Grouping.
EOG: Evolutionary Optimization of Granules.
IQP: integer quadratic programming.
CLP: Cell Layout Problem.

MOGA: Multi-Objective Genetic Algorithm.
Pc: probability of crossover.
Pm: probability of mutation.
GH: greedy heuristic.
RES: roulette–elitist strategy.
GN: generation number.
PS: population size.
LSOT: large scale optimization technique.

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Received August 2010
Accepted August 2010
Final acceptance in revised form August 2010