AN EVOLUTIONARY APPROACH FOR CMS DESIGN

Waqas Javaid[1*], Adnan Tariq[1], Iftikhar Hussain[2], Sahar Noor[2]

ABSTRACT

Cellular Manufacturing Systems (CMS) have been widely considered as the most efficient manufacturing systems in the case of medium variety and medium volume of production. The main advantage of CMS lies in the effective grouping of parts into families and machines in to corresponding groups as it results in minimizing the number of intercellular moves. Over the years, a number of efficient approaches have been developed by researchers to handle the Cell Formation Problem (CFP). Among these, a large number of approaches consist of Artificial Intelligence (AI) based techniques. The main advantage of such approaches is their ability to handle the CFP effectively both in terms of accuracy and computational effort. Following the same trend an evolutionary algorithm has been developed during this research by combining Standard Genetic Algorithm with a very effective Local Search Heuristic (LSH). The results show that it is efficient both in terms accuracy and speed of convergence (CPU time).

KEYWORDS: *Group Technology; Cellular Manufacturing; Cell Formation Problems; Genetic Algorithm*

INTRODUCTION AND LITERATURE REVIEW

Cellular Manufacturing (CM) is a concept of formulating part families and rearranging the relevant machines into respective cells. The concept of CM has gained popularity due to a number of advantages e.g. reduction in: setup time, lot size, inventory levels, flow time and material handling cost etc. these advantages are the direct influence of the hybrid nature of the Cellular Manufacturing System (CMS) that possesses the advantages of both job-shop and flow line manufacturing systems. Having so many benefits the design of CMS is still considered as a challenging task and the main challenge here is the effective part-machine grouping that minimizes the intercellular processing requirements of parts. To handle the Cell Formation Problem (CFP) a number of approaches have been developed over the past more than fifty years. These can mainly be classified as:Classification & Coding, Similarity Co-efficient, Array Based Clustering, Graph Partitioning, Mathematical Programming, Heuristics, and Artificial Intelligence(AI). Among these approaches AI-based techniques are the ones that remained the focus of researchers recently. Mungawatana[2002][1], Goncalves&Resende [2004][2] and Arora et al [2013][3] were all of the view that out of the many AI based techniques, Genetic Algorithm (GA) has been extensively used both in standard and hybrid forms, for the CFP. This is the reason that the focus of literature review, as far as this paper is concerned, is kept mainly on GA based approaches developed in the last decade.

Boulif&Atif [2006][4] presented a Branch-&-Bound (B&B)-enhanced GA for the manufacturing CFP. Initially the problem was solved using GA with binary encodings and later on to improve its performance a B&B enhancement was used. Results showed that GA with B&B enhancement performed better than the standard GA. James et al [2007][5] presented a Hybrid Grouping Genetic Algorithm (HGGA) for the cell formation problem. They developed a combination of Local Search Heuristic (LSH) with standard GA and used Grouping Efficacy (GE) as the measure of performance. Computational results showed that the tool was effective enough as it either exceeded or matched the solution quality of the results available in literature prior to this technique. A hybrid heuristic approach was presented by Wu et al [2009][6]. This approach was mainly a combination of Boltzmann Function and a mutation operator. By allowing the formation of singletons this approach reported an overall improvement in GE for 36% of the total tested benchmark problems.

A Grouping Genetic Algorithm (GGA) based approach was presented by Saleh&Moghaddam [2009][7]. On the basis of that limited computational experience, testing only 14 benchmark problems, the authors claimed that their approach is more flexible and equally efficient as compared to some of its predecessors. AnArtificial Neural Networks (ANN) based approach for the CFP

1 Department of Mechanical Engineering, Wah Engineering College, University of Wah, Quaid Avenue, Wah Cant, Punjab 47040, Pakistan*
2 Department of Industrial Engineering, University of Engineering & Technology, Peshawar, Pakistan

was presented by Pandian&Mahapatra [2009][8] for solving the CFP and integrating some production related data, such as processing sequence and operation times, into their design. The approach claimed to have improved the operational performance of the system by reducing the manufacturing lead times and costs related to inventory and material handling.

Rezaeian et al [2011][9] developed a hybrid approach by combining GA with ANN and solved the problem of converting a job shop into a CMS with the objective of minimizing the material handling cost. Computational experience showed that the approach performed better than standard GA and Simulated Annealing (SA) in finding out the optimum solutions for the problems that were randomly generated. Elbanani et al [2012][10] solved the CFP using GA in combination with a large neighborhood search algorithm. Authors claimed to reach the best solution in case of 31 out of the 35 widely known benchmark problems. Banerjee & Das [2012][11] developed a modified predator and prey genetic algorithm. The algorithm focuses on the local selection strategy and maintains a reasonable balance between the predator and prey population. The approach is reported to be effective in terms of avoiding premature convergence and getting the final machine part incidence matrix in comparatively lesser number of iterations.

Mutinigi & Onwubolu [2012][12] developed an approach based on grouping GA for solving an integrated model of CMS design and Layout generation. Shiyas & Pillai [2012][13] developed a non-linear programming model for grouping of machines in CM environment and then devised a GA based heuristic to solve the model. The objective of their research was to minimize the heterogeneity of the manufacturing cells. To prove the effectiveness of the approach a limited computational experience of only 7 benchmark problems and comparison of results against an even limited number of approaches was presented. Mutingi [2013][14] developed a fuzzy simulated algorithm to handle an integrated problem of cell formation and layout generation. On the basis of limited computational experience the author claimed that this approach can be used to handle other hard combinatorial optimization problems in industry.

Pydar & Mehrabad [2013][15] developed a linear fractional programming model for the CFP. They proposed a hybrid GA based algorithm, by combining GA with a Variable Neighborhood Search (GA-VNS) and keeping the number of cells as unknown, to solve the model. A comprehensive comparison of results of 35 benchmark problems with state of the art algorithms showed that GA-VNS outperformed all of them by obtaining best results for 28 benchmark problems. Zebet. al. [2016][16] developed a hybrid GA based algorithm by combining GA with Simulated Annealing (SA) where intensification power of SA is used to broaden the search space. The comparison of results revealed that 23 best results were obtained out of 35 benchmark problems by this algorithm.

From the above review it can very evidently be concluded that approaches incorporating AI have been very frequently used in literature to handle the CFP mainly because of their accuracy and speed of convergence. This was the basic motivation for the authors to develop an even more effective approach for CFP by combining GA with an efficient Local Search Heuristic. A thorough comparison with some of the latest techniques showed that the technique proposed in this paper is more accurate and quick as far as convergence on to the best solution is concerned.

MATHEMATICAL MODEL

The variables/ indices used in the formulation are defined as follows:

CN= Total number of Cells

M =Total number of Machines

X_i = Total number of 1's in Cell 'i'

P = Total number of Parts

G = Total no of 1's in Machine Part Incident Matrix (MPIM)

G_{voids}= Total number of 0's inside all the cells (Block Diagonal)

Z= variable (any)

M_n= Number of Machines in cell 'i'

P_n= Number of Parts in cell 'i'

G_{in}=Total number of 1's inside all the cells (Block Diagonals)

G_{out}= Accumulative number of intercellular moves.

G_{out}=G - G_{in}

The mathematical model for the approach developed hereis presented as follows. The algorithm has the ability to optimize the number of cells for each problem as well.

$$Objective = F = Maximize\,(GE) = Maximize\,(\frac{G - G_{out}}{G + G_{voids}}) \quad (1)$$

Subject to:

$$\frac{2}{M} \leq CN \leq \quad (2)$$

$$\sum_{i=1}^{NC} Xi \geq 1 \quad (3)$$

The constraint in eq. (2) ensures that the minimum number of cells remains 2, whereas the maximum number of cells must not exceed the total number of machines.

The constraint in eq. (3) ensures that at least one part and one machine are allocated to each cell. The rest of the variables included in the objective function and/or constraints can be determined as shown in eq, (4), (5), (6) and (7)

$$G = \sum_{c=1}^{M}\sum_{d=1}^{P} a_{c*d} \quad (4)$$

If α_{m*n}=1

$$Gvoids = \sum_{i-1}^{CN}\ \sum_{a-1}^{M_n}\ \sum_{d-1}^{P_n} Zi*c*d \quad (5)$$

If α_{i*c*d}=0 then Z_{i*c*d} = 1 else Z_{i*c*d}= 0

$$Gvoids = \sum_{i-1}^{CN}\ \sum_{a-1}^{M_n}\ \sum_{d-1}^{P_n} ai*c*d \quad (6)$$

$$G_{out} = G - G_{in} \quad (7)$$

METHODOLOGY

As cell formation problem is NP-hard therefore it is difficult to solve it in rational computational time by considering all the possible options. This is the reason that researchers try to develop/utilize search based heuristics while handling such problems. The technique presented here is a combination of GA with LSH to optimize the machine part grouping of realistically sized problems. The GA presented during this research employs integer based representation, multi-point crossover (60%), swap mutation (5%) and stochastic universal sampling (SUS) as the selection approach. The procedure is displayed in Fig 1 as follows:

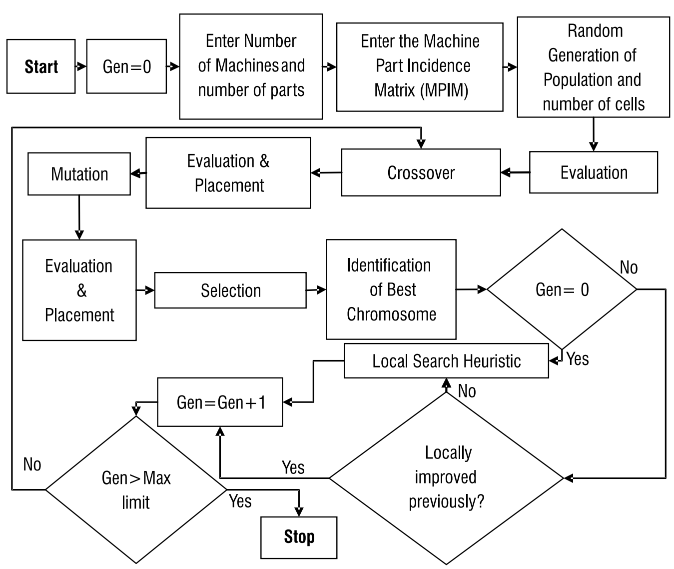

Figure 1: Methodology of HGA

Local Search Heuristic (LSH)

The hybrid nature of the algorithm, presented during this research, is due to the combination of standard GA with an LSH.Procedure is completely elaborated with the help of a flow diagram as shown in Fig 2. The uniqueness of this LSH is that it rearranges only those machines/ parts which are ill placed i.e. having more intercellular moves. This kind of strategy gives more accurate results.

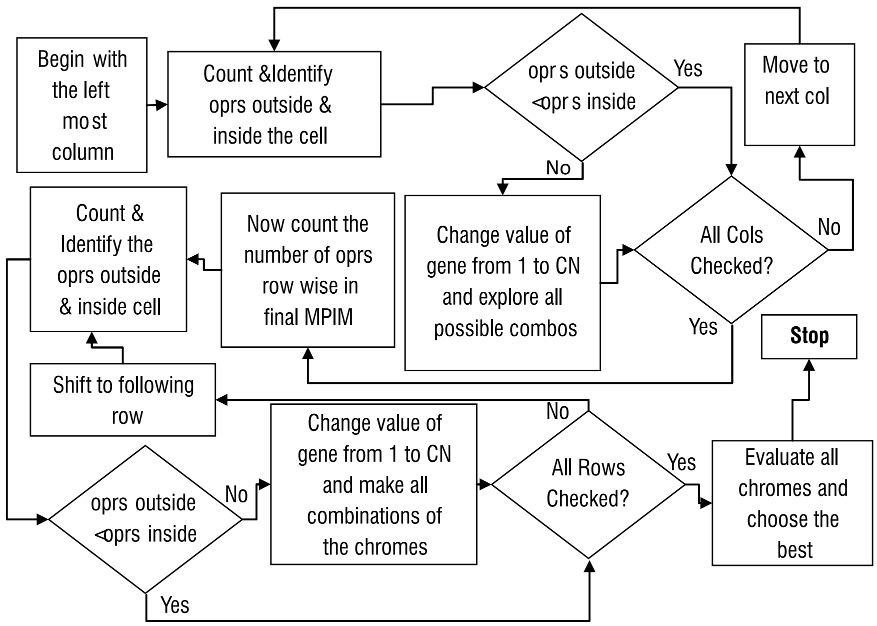

Figure 2: Local Search Heuristic (LSH)

Computational Results

To prove that the approach presented in this paper works better than the rest of the approaches available in literature a thorough comparison is presented in Table 5 and the techniques used (for comparison) are listed as follows.

1. ZODIAC(Chandrasekharan&Rajagopalan, [1987])[17]
2. GRAFICS(Srinivasan&Narenderan, [1991])[18]
3. GATSP(Cheng et al. [1998])[19]
4. GA(Onwubolu&Mutingi, [2001])[20]
5. EA(Goncalves&Resende [2004])[4]
6. HGGA(James et al. [2007])[5]
7. HGA(Tariq et al. [2009])[21]
8. GAA(Mahdaviet al. [2009])[22]
9. EnGGA(Tunnukij& Hicks [2009])[23]
10. HGDE(Noktehdanet al. [2010])[24]
11. SA(Paillaet al. [2010])[25]
12. GA-VNS(Payder&Mehrabad [2013])[15]
13. HSA-GA (Zeb et. al. [2016])[16]

It can be clearly observed in Table 1 that the approach developed during this research has outperformed almost all the techniques and remained equally competitive with the one(GA-VNS) recently reported, as both returned an equal number of best solutions i.e. 28. Since performance in comparison to GA-VNS seemed to be more or less the same therefore further analysis needs to be carried out. For this purpose, a head to head comparison of the two techniques (GA-VNS vs. This Approach), is presented in Table 2 and Fig. 3. This comparison is based both on accuracy and speed of convergence (CPU time). It shows that both the techniques are almost equivalent as far as

Table 1: Comparison of Results

S/ No.	Source	Prob. Size	ZO-DIAC	GRAFI-CS	GATSP	GA	EA	HGGA	HGA	GAA	EnG-GA	HGDE	SA	GA-VNS	HSA-GA	This Approach
01	King &Nakornchai (1982)[26]	5x7	73.68	73.68	-	-	73.68	82.35	73.68	-	82.35	82.35	75	82.35	82.35	82.35
02	Waghodekar&Sahu (1984)[27]	5x7	56.22	60.87	68	62.5	62.5	69.57	69.57	69.57	69.57	69.57	69.57	69.57	69.57	69.57
03	Seifoddini (1989)[28]	5x18	-	-	77.36	77.36	79.59	79.59	79.59	79.59	79.59	79.59	80.85	80.85	79.59	80.85
04	Kusiak (1992)[29]	6x8	-	-	76.92	76.92	76.92	76.92	76.92	76.92	76.92	76.92	79.17	79.17	76.92	79.17
05	Kusiak& chow (1987)[30]	7x11	39.13	53.12	46.88	50	53.13	60.87	58.62	60.87	60.87	60.87	60	60.87	60.87	60.87
06	Boctor (1991)[31]	7x11	-	-	70.37	70.37	70.37	70.83	70.37	70.83	70.83	70.83	70.83	70.83	70.83	70.83
07	Seifoddini& Wolfe (1986)[32]	8x12	68.3	68.3	-	-	68.29	69.44	68.3	-	69.44	69.44	69.44	69.44	69.44	69.44
08	Chan-drasekharan&Raja-gopalan (1986a)[33]	8x20	85.25	85.25	85.25	85.25	85.25	85.25	85.25	85.25	85.25	85.25	85.25	85.25	85.25	85.25
09	Chan-drasekharan&Raja-gopalan (1986b)[34]	8x20	58.33	58.13	58.33	55.91	58.72	58.72	58.72	58.72	58.72	58.72	58.72	58.72	58.72	58.72
10	Mosier & Taube (1985a)[35]	10x10	70.59	70.59	70.59	72.59	70.59	75	70.59	75	-	75	75	75	75	75
11	Chan & Milner (1982)[36]	10x15	92	92	92	92	92	92	92	92	-	92	92	92	92	92
12	Askin& Subrama-nian (1987)[37]	14x23	64.36	64.36	-	-	69.86	72.06	70.83	-	-	72.06	74.24	74.24	73.13	74.24
13	Stanfel (1985)[38]	14x24	65.55	65.55	67.44	63.48	69.33	71.83	70.51	71.83	-	71.83	72.86	72.86	71.83	72.86
14	McCormick et al. (1972)[39]	16x24	32.09	45.52	-	-	52.58	52.75	51.96	-	53.26	53.41	53.33	53.85	53.26	53.85
15	Srinivasan et al. (1990)[40]	16x30	67.83	67.83	-	-	67.83	68.99	67.83	-	68.99	68.99	69.92	70.76	68.99	70.76
16	King (1980)[41]	16x43	53.76	54.39	53.89	86.25	54.86	57.53	54.86	56.13	57.53	57.53	57.98	57.64	57.53	57.64
17	Carrie (1973)[42]	18x24	41.84	48.91	-	-	54.46	57.73	54.95	-	57.73	57.73	57.73	57.73	57.73	57.73
18	Moiser& Tube (1985b)[43]	20x20	21.63	38.26	37.12	34.16	42.94	43.18	43.45	42.94	-	43.45	43.97	43.26	43.45	43.26
19	Kumar et al. (1986)[44]	20x23	38.96	49.36	46.62	39.02	49.65	50.81	49.65	-	-	50.81	50.81	50.81	50.81	50.81
20	Carrie (1973)[42]	20x35	75.14	75.14	75.28	66.3	76.22	77.91	76.14	77.91	77.91	77.91	79.38	78.4	78.4	78.4

21	Boe& Cheng (1991)[45]	20x35	-	-	55.14	44.44	58.07	57.98	58.38	-	57.98	57.98	58.79	58.15	58.38	58.38
22	Chan-drasekharan&Raja-gopalan(1989a,b)[46]	24x40	100	100	100	100	100	100	100	100	100	100	100	100	100	100
23	Chandrase-karan&Rajagopal-an(1989a,b)	24x40	85.11	85.1	85.1	85.11	85.11	85.11	85.11	85.11	85.11	85.11	85.11	85.11	85.11	85.11
24	Chan-drasekharan&Raja-gopalan (1989a,b)	24x40	37.85	73.51	73.51	73.03	73.51	73.51	73.51	73.51	73.51	73.51	73.51	73.51	73.51	73.51
25	Chan-drasekharan&Raja-gopalan (1989a,b)	24x40	20.42	43.27	43.27	37.62	51.88	53.29	52.5	52.87	53.29	53.29	53.29	53.29	53.29	53.29
26	Chan-drasekharan&Raja-gopalan (1989a,b)	24x40	18.23	44.51	44.67	34.76	46.69	48.95	46.84	48.95	48.95	48.95	48.57	48.95	48.95	48.95
27	Chan-drasekharan&Raja-gopalan (1989a,b)	24x40	17.61	41.67	42.5	34.06	44.75	47.26	44.85	47.26	46.58	47.26	46	47.26	46.58	47.26
28	McCormick et al. (1972)[39]	27x27	52.14	47.37	-	-	54.27	54.02	54.31	-	54.82	-	54.82	54.82	54.82	54.82
29	Carrie (1973)[42]	28x46	33.01	32.86	-	-	44.37	46.91	46.43	-	-	-	47.68	46.91	47.7	46.91
30	Kumar &Vannelli (1987)[47]	30x41	33.46	55.43	53.8	40.96	58.11	63.31	60.74	-	63.31	63.31	62.86	63.31	63.31	63.31
31	Stanfel (1985)[38]	30x50	46.06	56.32	56.61	48.28	59.21	59.77	59.66	60.12	-	59.77	59.66	60.12	60.12	60.12
32	Stanfel (1985)[38]	30x50	21.11	47.96	45.93	37.55	50.48	50.83	50.51	50.83	-	-	50.55	50.83	50.83	50.83
33	King &Nakornchai (1982)[26]	36x90	32.73	39.41	-	-	42.12	46.35	44.67	-	-	-	47.93	46.35	48.07	46.35
34	McCormick et al (1972)[39]	37x53	52.11	52.21	-	-	56.42	60.64	59.6	-	60.64	60.64	61.16	60.64	60.64	60.64
35	Chan-drasekharan&Raja-gopalan (1987)[17]	40x100	83.92	83.92	84.03	83.9	84.03	84.03	84.03	84.03	-	-	84.03	84.03	84.03	84.03
	Best Results		04	04	05	04	07	18	08	15	15	17	24	28	23	28

Table 2: Comparison of GA-VNSwith This Approach

S/No.	Source	Size	GA-VNS Approach			This Approach		
			No. of Cells	GE	CPU Time (sec)	No. of Cells	GE	CPU Time (sec)
1	King &Nakornchai (1982)[26]	5x7	2	82.35	0.11	2	82.35	0.47
2	Waghodekar&Sahu (1984)[27]	5x7	2	69.57	0.16	2	69.57	0.29
3	Seifoddini (1989)[28]	5x18	3	80.85	0.11	3	80.85	0.64
4	Kusiak (1992)[29]	6x8	3	79.17	0.14	3	79.17	0.45
5	Kusiak& chow (1987)[30]	7x11	5	60.87	0.89	5	60.87	0.77
6	Boctor (1991)[31]	7x11	4	70.83	0.74	4	70.83	0.85
7	Seifoddini& Wolfe (1986)[32]	8x12	4	69.44	0.84	4	69.44	0.83
8	Chandrasekharan&Rajagopalan (1986a)[33]	8x20	5	85.25	0.93	3	85.25	1.39
9	Chandrasekharan&Rajagopalan (1986b)[34]	8x20	2	58.72	0.96	2	58.72	1.42
10	Mosier & Taube (1985a)[35]	10x10	5	75	1.24	5	75	1.51
11	Chan & Milner (1982)[36]	10x15	3	92	1.54	3	92	2.6
12	Askin& Subramanian (1987)[37]	14x23	7	74.24	5.65	7	74.24	5.63
13	Stanfel (1985)[38]	14x24	7	72.86	8.76	7	72.86	8.67
14	McCormick et al. (1972)[39]	16x24	9	53.85	12.34	9	53.85	8.53
15	Srinivasan et al. (1990)[40]	16x30	6	70.76	15.4	6	70.76	9.01
16	King (1980)[41]	16x43	9	57.64	17.42	9	57.64	11.66
17	Carrie (1973)[42]	18x24	9	57.73	24.23	9	57.73	17.28
18	Moiser& Tube (1985b)[43]	20x20	5	43.26	19.89	5	43.26	16.32
19	Kumar et al. (1986)[44]	20x23	7	50.81	24.23	7	50.81	13.83
20	Carrie (1973)[42]	20x35	5	78.4	31.75	5	78.4	18.76
21	Boe& Cheng (1991)[45]	20x35	5	58.15	43.57	5	58.38	11.04
22	Chandrasekharan&Rajagopalan (1989a,b)[46]	24x40	7	100	56.43	7	100	17.22
23	Chandrasekaran&Rajagopalan(1989a,b)	24x40	7	85.11	71.69	7	85.11	17.71
24	Chandrasekharan&Rajagopalan (1989a,b)	24x40	7	73.51	82.5	7	73.51	23.74
25	Chandrasekharan&Rajagopalan (1989a,b)	24x40	11	53.29	74.19	11	53.29	69.97
26	Chandrasekharan&Rajagopalan (1989a,b)	24x40	12	48.95	53.29	12	48.95	84.31
27	Chandrasekharan&Rajagopalan (1989a,b)	24x40	12	47.26	83.65	12	47.26	130.15
28	McCormick et al. (1972)[39]	27x27	8	54.82	98.81	8	54.82	37.83
29	Carrie (1973)[42]	28x46	10	46.91	95.47	10	46.91	132.11
30	Kumar &Vannelli (1987)[47]	30x41	14	63.31	118.21	14	63.31	227.14
31	Stanfel (1985)[38]	30x50	13	60.12	151.72	13	60.12	255.15
32	Stanfel (1985)[38]	30x50	14	50.83	167.23	14	50.83	279.79
33	King &Nakornchai (1982)[26]	36x90	17	46.35	276.22	17	46.35	611.82
34	McCormick et al (1972)[39]	37x53	3	60.64	245.68	3	60.64	48.01
35	Chandrasekharan&Rajagopalan (1987)[17]	40x100	10	84.03	210.43	10	84.03	223.07
Total number of improved results		-	-	00	17	-	01	18

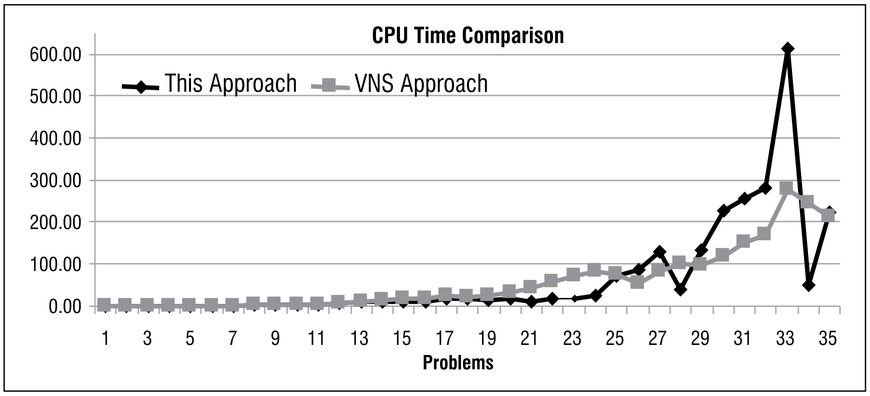

Figure 3: CPU Time Comparison (GA-VNS vs. This Approach)

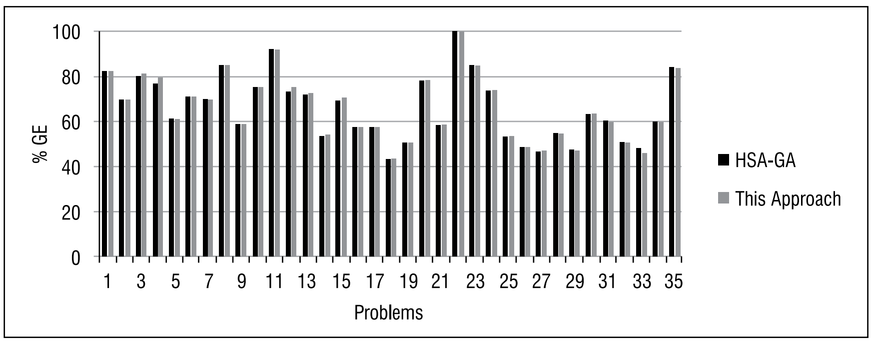

Figure 4: GE Comparison (HSA-GA vs. This Approach)

accuracy is concerned apart from just one instance(Problem # 21), where the approach presented in this paper has returned a larger GE value. For the second part of the comparison that is based on CPU time consumption, a system having2.7 GHz Core2duo processorwith 4 GB Ram has been used. These system specifications are exactly the same used by Pydar&Mehrabad [2013][15]. The results show that in 18 benchmark problems (more than 50%) thistechnique consumed lesser amount of CPU time.To break it down further, the same comparison of CPU time consumption has been carried out by considering only the last18 problems (from 18 to 35). The reason of selecting this group of problems (18 to 35) is that here the problem sizes are larger and more ill-structured as compared to the first 17 problems. Here also the results are in favor of this approach as it has performed better in case of 10 (58.82%) problems. This proves that the approach presented in this paper has not just outperformed a host of other techniques listed above but also performed comparatively better against GA-VNS which has been considered as one of the most effective techniques, recently developed.

The last two columns of Table 1 and graphical representation in Figure 4, shows a comparison between this approach and HSA-GA which is the most recently published approach. Out of the total of 35 benchmark problems,HSA-GA could only score 23 best results in comparison to 28 scored by this approach. This proves the effectiveness and consistency of the approach developed during this research as it has outperformed 13 well-known approaches developed over the last more than 25 years.

CONCLUSION

The main aim of this research was to develop an evolutionary algorithm for solving the CFP that can compete with some of the well-known and recently developedapproaches. For this purpose an evolutionary approach was developed during this research by combining GA with an effective Local Search Heuristic (LSH). The approach was used to solve the all famous 35 benchmark problems from literature. The results are compared with 13 highly ranked techniques from literature. The comparison shows that the approach presented in this paper has easily outperformed all the techniques while remained equally competitive with GA-VNS (Pydar&Mehrabad [2013])[15] as both recorded an equal number of best solutionsi.e.28. To investigate it further a head-to-head comparison of this approach and GA-VNS has also been carried out. This comparison shows that the approach presented here has performed better than GA-VNS both in terms of accuracy and speed of convergence.

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