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A Hybrid Algorithm for Multi-Objective Optimization of Minimizing Makespan and Total Flow Time in Permutation Flow Shop Scheduling Problems

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In this work, a hybrid algorithm has been proposed to solve bi-objective permutation flow shop scheduling problem. The primary concern of flow shop scheduling problem considered in this work is to obtain the best sequence, which minimizes the makespan and the total flow time of all jobs. Bi-objective issues are comprehended by doling out uniform weight to every objective function in view of its preference or determining every competent solutions. In the flow shop scheduling environment, many meta-heuristic algorithms have been used to find optimal or near-optimal solutions due to the computational cost of determining exact solutions. This work provides a hybridization of genetic algorithm and simulated annealing algorithm (HGASA) based multi-objective optimization algorithm for flow shop scheduling. The proposed HGASA algorithm is used to solve a bi-objective problem that minimizes the makespan and the total flow time. The performance of the proposed algorithm is demonstrated by applying it to benchmark problems available in the OR-Library. The test results show that the HGASA algorithm performed better in terms of searching quality and efficiency than other meta-heuristic algorithms.

KEYWORDS: Permutation Flow shop scheduling, Hybrid algorithm, Makespan, Total Flow time, Benchmark.

1. Introduction

In permutation flow shop scheduling, '*n*' jobs must be processed on '*m*' machines in the same Order sequence. The operation succession is the same for all jobs. The permutation flow shop scheduling (PFSSP) has a broad foundation in assembling frameworks and has pulled in numerous analysis consideration by Johnson [10]. Numerous researches for single objective FSSPs result in a schedule to minimize the makespan. The traditional ways to solve single-objective FSSP can be predominantly partitioned into two classes, to be specific, exact and approximation techniques. For a limited-wait constraints, complex hybrid flow-shop scheduling problem was solved with discrete time exact arrangement approach by Gicquel et al. [6], and a modified teaching–learning-based optimization algorithm has been used to solve bi-objective re-entrant hybrid flow shop scheduling by Shen et al. [20]. Later, Jeen Robert and Rajkumar [8] proposed a hybrid algorithm for minimizing makespan in the PFSSP. Two-machine and three-machine flow shop scheduling problem is solved using branch-and-bound (B&B) algorithm [7]. Campbell et al. [4] built up a heuristic algorithm for *n*-job m-machine sequencing problem with a goal of minimizing total flow time. A general schedule for *n* jobs with m machines is *(n!)m*. In this situation, just *n!* schedules must be considered to stay away from job flow. The performance measures of flow shop scheduling are makespan, total flow time and tardiness and so on. In flow shop environment, solving a single objective problem is very tedious one. Majority of studies for the flow shop scheduling problem focuses to minimize makespan. However, there are other important objectives than makespan for the flow shop scheduling problem. For example, the total flow time, the total machine idle time are very important performance measures in minimizing total scheduling cost. Hence, we consider the flow shop scheduling problem with the objectives of makespan and total flow time in this study. Weishi et al. [23] described a self-guided differential evolution with a neighborhood search for permutation flow shop scheduling. Rajendran [14] has developed a heuristic algorithm with the objective of minimizing the makespan and the total flow time for bi-objective flow shop scheduling problem. Nagar et al. [11] developed a combined hybrid algorithm to solve PFSSP with better minimization of makespan and average total flow time. Rajkumar and Shahabudeen [9, 16] described an EGA & IGA algorithm to solve the PFSP. Wang et al. [22] proposed a hybrid harmony search algorithm for solving flow shop benchmark problems. Carbon-efficient scheduling of flow shops by multi-objective optimization was proposed by Ding et al. [5] for the permutation flow shop scheduling environment. Abdolrazzagh et al. [1] presented a robust intelligent technique to produce the initial population close to the optimal solution for the job-shop scheduling problem. A branch and bound algorithm as in [25] is introduced in bi-objective flow shop scheduling field to minimize the weighted sum of total flow time and makespan. The author tried randomly generated population size problem and reported that the developed meta-heuristic algorithm is more fruitful on problem instances with 20 jobs. Rajendran and Ziegler [15] created max–min ant system (MMAS) and populace based ant colony optimization (PACO) algorithms to tackle flow shop scheduling problem with the target of minimizing the total flow time and makespan. Ravindran et al. [18] have been created a hybrid algorithm for solving bi-objective PFSP (HAMC1, HAMC2, and HAMC3) to minimize the total flow time and makespan. The results produced by HAMC's are well contrasted with CR multi-criterion (MC) heuristics and CR heuristics. Allouche et al. [2] proposed trade off programming which has fulfillment capacities for fathoming multi-objective scheduling problem with the goal of minimizing complete lateness, makespan and total flow time. Rajendran and Ziegler [13] created a multi-objective ant colony optimization (ACO) to deliver non-dominated arrangement with the target of minimizing total flow time and makespan in PFSSP. Rajkumar and Shahabudeen [17] developed a meta-heuristic algorithm to solve bi-objective flowshop scheduling problem. Multi-Objective Ant Colony System Algorithm (MOACSA) to minimize the destinations of both total flow time and makespan in permutation flow shop scheduling is discussed in [24]. They concluded that proposed MOACSA performs better than CR (MC) algorithm, HAMC algorithms and GA for said multi-objective flow shop scheduling problem. Nearest Neighbor (NN) and Ant Colony Optimization (ACO) algorithm is used to minimize the terminuses of both CPU time and makespan in permutation flow shop scheduling [3].

Recently, Sanjeev Kumar et al. [19] developed a modified gravitational emulation local search (MGELS) algorithm to minimize both makespan and total flow time. The proposed methodology is carried out with the flow shop benchmark problem, and the execution of MGELS algorithm is contrasted with CR algorithm, HAMC1, HAMC2, HAMC3, CR (MC), Multiple Objective Adaptive Clonal Selection Algorithm (MOACSA), GA, and DT algorithm. In this present work, a hybrid algorithm is proposed that hybridizes the Genetic Algorithm (GA) and the simulated Annealing (SA) algorithm. The Genetic algorithm acts as local search scheme and the Simulated Annealing algorithm acts as a global search scheme by accepting some inferior count values. Moreover, in proposed HGASA, the sub chromosomal level crossover and mutation is implemented to get better results and this seed is given to the SA algorithm to get further improvements which avoids the worst solution. So it is believed that HGASA can achieve satisfactory improvement for PFSSPs. Then the performance of the proposed algorithm is tested with flow shop scheduling benchmark problems. The results obtained by the proposed HGASA are compared with earlier reported results of CR algorithm, HAMC1, HAMC2, HAMC3, CR (MC), MOACSA, GA, and DT algorithm. Test results show that the proposed algorithm is more efficient than other algorithm and best suited for large sized problems.

The rest of this paper is organized as follows: Section 2 presents the mathematical model of PFSP. Section 3 presents the flowchart and procedure of proposed HGSSA for PFSP. Section 4 shows the experimental results and comparisons between HGSSA and other algorithms. Section 5 summarizes the conclusions of this work.

2. Mathematical Model of PFSP

In the present paper, bi-objective optimization for minimizing the makespan and total flow time for established PFSP is considered. The detailed explanation of PFSP is given in sub sequent section.

2.1. Permutation Flow Shop Scheduling Problem (PFSP)

The main objective of the permutation flow shop scheduling problem is to find a suitable job sequence that minimizes makespan and total flow time. The objective of this work is to develop a HGASA and hence to find the optimal or near optimal solution sequence in flow shop scheduling by minimizing makespan and total flow time. In PFSP, there are *'n'* independent jobs (permutation job set j = 1, 2,. . .n) that should be processed on *'m'* machines (k = 1,2,. . .m) and B_k is an inter-mediate buffer between two consecutive machines. All the machines (M_1, M_2,.....,M_m) follow the same job sequence till the end of all operations. This means that, the r^{th} task of job j is executed by machine M_r with processing time $T(r, j)$, where $1 \leq r \leq m$, and $1 \leq j \leq k$. Therefore, the completion times of jobs on the machines, makespan and the total flow time (TFT) of the jobs in the flow shop scheduling can be intended as follows:

The following notations are used in PFSP:

T(r, j)	Processing time for job r on a given machine j (r=1, 2,.....n), (j= 1, 2.....m)
n	total number of jobs to be scheduled
m	total number of machines in the process
$Cmax$	makespan
r	the occupation sequenced in the i^{th} position of a schedule
$C(r, j)$	the completion time of jobs r on machine j

The multi-objective flow shop scheduling problem consists of scheduling n jobs with given processing time on m machines. The flow shop problem has a fundamental assumption, i.e. n jobs are processed on m machines in the same order. The initial machine setup time is not considered for determining the makespan value calculation. The following equations are used to find the completion time of the job schedule:

$$C(1, 1) = T(1, 1) \tag{1}$$

$$C(1, j) = C(1, j-1) + T(1, j) \tag{2}$$

$$C(r, 1) = C(r-1, 1) + T(r, 1) \tag{3}$$

$$C(r, j) = Max(C(r, j-1), C(r-1, j)) + T(r, j) \tag{4}$$

$$TFT = \sum_{i=1}^{n} C(i, m). \tag{5}$$

In Eq. (4), $T(r, j)$ represents the finishing time of r^{th} job of the j^{th} work on machine M_r, $C(r, j)$ represents the most extreme execution time of the j^{th} work on machine M_r, $1 \leq r \leq m$ and $1 \leq j \leq k$, where k is the total number of jobs, and m is the total number of machines, then $C(m, k)$ represents "Makespan", where $C(i, m)$ is the finishing time of the i^{th} job in the last machine 'm', i.e. Total flow time (TFT) is the total completion time of all jobs spent on the production system.

3. The Proposed Hybrid Algorithm (HGASA)

We proposed a hybrid (HGASA) meta-heuristic algorithm, which can be used for the minimization of makespan and total flow time in the PFSP. Hybridization indicates combining of two or more algorithms to solve a given complex problem. Our algorithm hybridizes the Genetic Algorithm and the simulated annealing algorithm to reach global best (gbest) or near to global solution. In HGASA, Genetic Algorithm acts as local search scheme, and the Simulated Annealing algorithm acts as global search scheme by accepting some inferior count values. Moreover, in the proposed HGASA, the sub chromosomal level crossover and mutation are implemented to get better results, and this seed is given to SA algorithm to get further improvements by avoiding worst solution. As a result, it is believed that HGASA can achieve satisfactory improvement in PFSPs. The framework for the HGASA algorithm to the Permutation Flow Shop Scheduling Problem is clearly illustrated in Fig. 1. for the bi-objective optimization of makespan and total flow time minimization. The steps involved in the proposed HGASA algorithm are stated below.

Step 1: Generate an initial population using Nawaz et al. [12] (NEH) algorithm.

Step 2: Initialization; Define the size of population = 1500; number of generations =200; crossover probability=0.05; mutation probability=0.05.

Step 3: Evaluate the Fitness function value of each chromosome by $f(x) = \frac{1}{1+(0.5C_{max}+0.5TFT)}$, where C_{max}= makespan and TFT= $C(i, m)$.

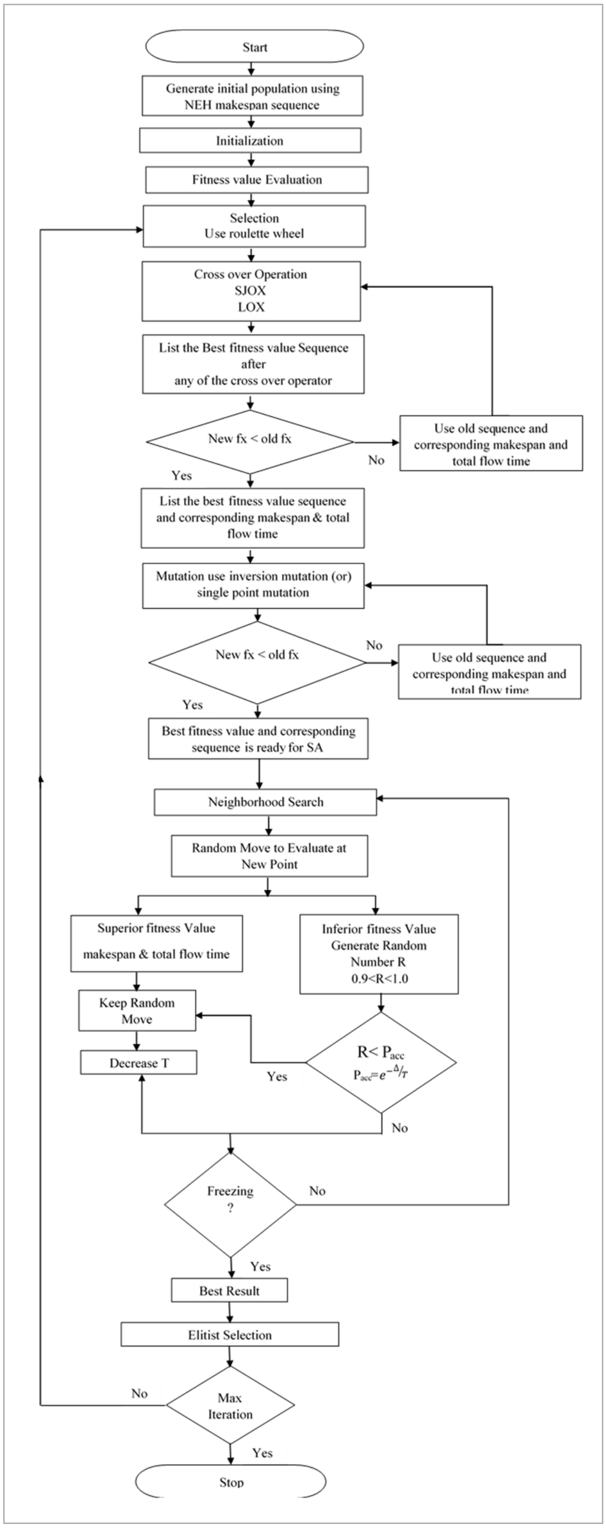
Step 4: Perform the following crossover operation: list the best *f(x)* sequence that minimizes both makespan and total flow time.

Similar Job Order Crossover (SJOX)

SJOX crossover is based on the idea of identifying and maintaining building blocks in the offspring. In this way similar blocks or occurrences of jobs in

Figure 1

The structure of the HGASA for PFSP



both parents are passed over to child unaltered. If there are no similar blocks in the parents the crossover operator will behave like the single-point order crossover. The SJOX crossover operator can be explained as follows:

Step 1: Both parents are examined on a position-by-position basis. Identical jobs at the same positions are copied over to both offspring.

Step 2: The offspring directly inherits all jobs from the corresponding parents up to a randomly chosen cut point. That is, Child1 inherits directly from Parent1 and Child2 from Parent2.

Step 3: Missing elements at each offspring are copied in the relative order of the other parent and it is shown in Table 1.

Table 1

Similar Job Order Crossover (SJOX)

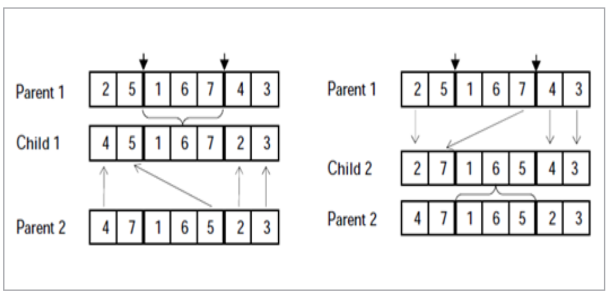
Parent1	3	5	6	4	2	7	8	9	1
Offspring1	3	5	6	4	2	9	8	7	1
Offspring2	3	9	8	4	2	5	6	7	1
Parent2	3	9	8	4	2	5	7	6	1
	cut point								

Linear Order Crossover (LOX)

Linear Order Crossover (LOX) tries to preserve both the relative positions between genes as much as possible and the absolute positions relative to the extremities of parents and it is shown in Fig. 2.

Figure 2

Linear order crossover



Step 1. Select a subsequence of operations from one parent at random.

Step 2. Produce a proto-offspring by copying the subsection sequence into the corresponding positions of it.

Step 3. Delete the operations which are already in the subsequence from the second parent. The resulted sequence of operations contains the operations that the proto-offspring needs.

Step 4. Place the operations into the unfixed positions of the proto-offspring from left to right according to the order of the sequence to produce an offspring.

Step 5: Mutation produces an offspring arrangement by arbitrarily altering the parent's qualities. In this present algorithm, two different types of mutation operators are introduced, namely inverse mutation and single point mutation.

Inverse Mutation

In a sequence, two positions i and j are randomly selected. The portion of the sequence between these two positions is inverted to get a new mutated sequence. The new sequence represents the sequence of operations after mutation. If the makespan of the mutated sequence is less than the makespan of the original sequence, the old sequence is replaced by the new sequence. (Example. Mutation positions between 2 and 8).

Original Sequence

8 9 7 6 4 5 3
2 1

Mutated Sequence

8 4 3 2 7 9 6
5 1

Single Point Mutation

A random operation is selected in the sequence and moved to another random position in the sequence. If the makespan of the resulting sequence is less than that of the previous one, it replaces the previous sequence.

Before single point mutation

8 9 7 6 4 5 3
2 1

After single point mutation

8 9 7 4 5 3 2
1 6

Step 6: Simulated annealing begins with a neighborhood search by defining initial parameters.

Step 7: Random move to evaluate at the new point. The obtained fitness function values are compared with existing fitness function values. If the obtained value is the superior one, then repeat the same process to get further better results. The advantage of the simulated annealing process is that the inferior solutions are also accepted to get the global best value. The probability of inferior value acceptance is measured by $P_{acc} = e^{\frac{(-\Delta)}{T}}$ where Δ is objective difference = $(f(x')\text{-}f(x))$, where x *is the current makespan*, x' *is the neighborhood of* x and T is the temperature. In the proposed HGASA algorithm, the random number is generated in the range of 0.9 to 1.

Step 8: Check for freezer count by reducing the system temperature according to the cooling schedule.

Step 9: List the best fitness function value and corresponding sequence by indicating makespan and total flow time.

Step 10: The procedure is stopped when the temperature reaches the final set temperature or it reach the maximum number of iterations.

4. Experimental Results and Comparisons

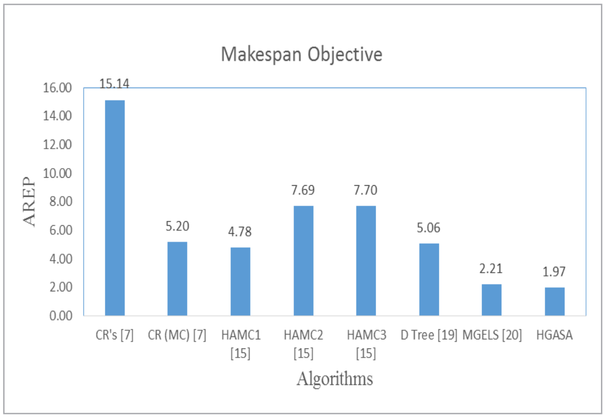
In this article, the proposed HGASA algorithm is coded in Matlab 2009 programming tool and tried on an Intel Core i-3, 1.6 GHz with 4 GB RAM PC equipment. It has been tried with 28 flow shop benchmark problems, jobs sizes from 20, 50, and 100 and machines sizes from 5, 10, and 20. These benchmark problems are taken from Taillard [21]. Each instance can be characterized by the following parameters: number of jobs (n) and number of machines (m). Each instance has been subjected for 200 iterations to find the best fitness function value. The performance analysis of the proposed HGASA algorithm is described in Table 2. Equal weights are considered for each objective (0.5, 0.5) as the MS and TFT objectives are conflicting in nature. The equal weights are considered in Yagmahan and Yenisey [22] and Balasundaram et al. [3]. Considering makespan as an objective, 28 benchmark problems have been solved. Out of these problems, HGASA algorithm produced 16 best makespan solutions, whereas MGELS algorithm produced 8 best solutions. Decision Tree algorithm produced one best solution, and CR (MC) produced three best solutions. Table 3 gives the percentage improvement in makespan value using HGASA over earlier literature results. Moreover, the Average Relative Error Percentage (AREP) of the proposed HGASA algorithm is (1.97) less than that of all different methodologies such as MGELS, DT algorithm, HAMC3, HAMC2, HAMC1, CR (MC), and CR in view of makespan objective and it is shown in Fig. 3. The performance of the algorithms is given using Average Relative Error Percentage (AREP) equation

$$f(x) = \frac{1}{1+(0.5C_{\max} + 0.5TFT)}, \quad (6)$$

where C^* is the Best makespan.

Figure 3

A comparison of AREP of HGASA algorithm with other methods for makespan



In view of flow time calculation, the proposed HGASA algorithm has produced 10 best flow time solutions, whereas MGELS algorithm also produced 10 best solutions. Decision Tree algorithm has produced six best solutions, whereas HAMC 2 algorithm has produced one best flow time value and CR algorithm has produced one best solution. Table 4 gives the percentage improvement in total flow time value using HGASA over earlier literature results. Besides, the average REP (AREP) of the proposed HGASA algorithm is (0.69) less than that of all different methodologies such as MGELS, DT calculation, HAMC3, HAMC2, HAMC1, CR (MC), and CRs and it is shown in Fig. 4.

Table 2
Performance analysis of the proposed HGASA algorithm method with the existing methods

Prob-lem No	CR's [14]		CR (MC) [14]		HAMC1 [13]		HAMC2 [13]		HAMC3 [13]		Decision Tree [22]		MGELS [21]		HGASA	
	MS	TFT	MS	TFT	MS	TFT	MS	TFT	MS	TFT	MS	TFT	MS	TFT	MS	TFT
ta001	1377	14,361	1359	15,196	1297	14,274	1324	14,150	1307	14,193	1297	14105	1160	14220	1305	14199
ta002	1468	15,947	1378	18,204	1373	16,483	1409	15,386	1409	15,386	1386	15403	1364	15354	1397	15405
ta003	1379	14,261	1230	15,697	1206	13,858	1210	13,798	1210	13,798	1190	13759	1196	13464	1135	13973
ta004	1548	16,268	1393	17,037	1402	16,086	1423	15,770	1418	15,773	1413	15652	1373	15569	1313	16106
ta005	1387	19,884	1307	15,429	1334	14,897	1387	13,771	1387	13,779	1387	13726	1387	13660	1338	13619
ta006	1411	14,251	1282	15,030	1238	13,853	1281	13,389	1281	13,413	1312	13732	1228	13582	1260	13179
ta007	1381	13,972	1387	15,925	1322	14,215	1359	13,955	1332	13,959	1299	13872	1306	13838	1276	13867
ta008	1404	14,278	1344	15,716	1287	14,405	1404	14,269	1404	14,278	1242	14133	1254	14469	1254	14185
ta009	1425	14,907	1335	15,556	1307	15,823	1382	14,835	1382	14,835	1308	14863	1300	14660	1295	14600
ta010	1284	13,374	1191	14,622	1195	13,676	1298	13,204	1221	13,232	1198	13185	1193	13382	1170	13320
ta011	1887	22,526	1711	23,125	1774	22,427	1812	22,202	1787	22,234	1740	22078	1680	21298	1740	21327
ta012	2121	24,139	1916	26,526	1791	23,461	1817	23,003	1832	23,046	1870	22927	1747	23025	1743	23113
ta013	1786	20,654	1617	21,572	1643	21,818	1784	20,577	1783	20,608	1658	20600	1506	20156	1593	20148
ta014	1628	19,440	1533	20,761	1531	19,599	1595	19,276	1584	19,332	1587	19058	1548	18952	1468	19190
ta015	2693	34,484	1588	20,875	1722	19,740	1557	20,510	1586	19,463	1532	19373	1483	18975	1507	18875
ta016	1835	20,861	1565	21,109	1612	20,064	1674	19,751	1667	19,846	1647	19758	1621	19952	1616	19552
ta017	1659	19,422	1622	20,306	1594	19,268	1624	18,718	1628	18,992	1622	18967	1616	19007	1544	18850
ta018	1878	21,336	1800	23,991	1631	21,596	1659	20,958	1659	21,049	1669	20815	1671	21163	1605	20928
ta019	1851	20,859	1717	22,572	1769	21,595	1842	20,823	1823	20,851	1717	20903	1625	20767	1611	20972
ta020	1878	21,901	1831	25,034	1744	21,819	1831	21,541	1793	21,573	1795	21817	1738	20793	1725	21000
ta021	2700	35,405	2610	38,650	2491	36,027	2539	34,907	2546	35,159	2531	34830	2510	34638	2435	34404
ta022	2600	34,326	2301	35,426	2491	33,304	2491	33,304	2586	34,319	2363	32749	2285	32804	2283	32266
ta023	2550	33,519	2411	35,152	2422	33,556	2433	32,900	2506	33,411	2649	34328	2396	32857	2588	34411
ta024	2815	36,130	2471	37,081	2567	37,870	2693	35,475	2722	35,810	2453	32689	2438	32635	2282	31987
ta025	2518	33,729	2427	35,285	2420	35,029	2453	33,198	2493	33,682	2462	35735	2376	33137	2584	33320
ta026	2730	35,135	2466	37,142	2557	36,712	2641	34,742	2663	35,089	2434	34035	2416	34017	2359	33267
ta027	2582	33,025	2174	36,126	2448	34,389	2528	33,402	2515	33,484	2473	33615	2013	33362	2434	33569
ta028	2472	33,526	2418	34,076	2464	33,565	2473	33,479	2472	33,500	2554	33321	2513	33583	2499	33534

CR: cognitive radio; MC: multi-criterion; HAMC: hybrid algorithm for multi-criterion; MGELS: modified gravitational emulation local search; AREP: average relative error percentage; HGASA: Hybrid genetic algorithm simulated annealing algorithm.

Table 3
Percentage improvement in makespan value using HGASA over earlier literature results

Problem No	n x m	CR's [14]	CR (MC) [14]	HAMC1 [13]	HAMC2 [13]	HAMC3 [13]	D Tree [22]	MGELS [21]	HGASA
ta001	20 x 5	18.71	17.16	11.81	14.14	12.67	11.81	0.00	12.50
ta002	20 x 5	7.62	1.03	0.66	3.30	3.30	1.61	0.00	2.42
ta003	20 x 5	21.50	8.37	6.26	6.61	6.61	4.85	5.37	0.00
ta004	20 x 5	17.90	6.09	6.78	8.38	8.00	7.62	4.57	0.00
ta005	20 x 5	6.12	0.00	2.07	6.12	6.12	6.12	6.12	2.37
ta006	20 x 5	14.90	4.40	0.81	4.32	4.32	6.84	0.00	2.61
ta007	20 x 5	8.23	8.70	3.61	6.50	4.39	1.80	2.35	0.00
ta008	20 x 5	13.04	8.21	3.62	13.04	13.04	0.00	0.97	0.97
ta009	20 x 5	10.04	3.09	0.93	6.72	6.72	1.00	0.39	0.00
ta010	20 x 5	9.74	1.79	2.14	10.94	4.36	2.39	1.97	0.00
ta011	20 x 10	12.32	1.85	5.60	7.86	6.37	3.57	0.00	3.57
ta012	20 x 10	21.69	9.93	2.75	4.25	7.97	7.29	0.23	0.00
ta013	20 x 10	18.59	7.37	9.10	18.46	18.39	10.09	0.00	5.78
ta014	20 x 10	10.90	4.43	4.29	8.65	7.90	8.11	5.45	0.00
ta015	20 x 10	81.59	7.08	16.12	4.99	6.95	3.30	0.00	1.62
ta016	20 x 10	17.25	0.00	3.00	6.96	6.52	5.24	3.58	3.26
ta017	20 x 10	7.45	5.05	3.24	5.18	5.44	5.05	4.66	0.00
ta018	20 x 10	17.01	12.15	1.62	3.36	3.36	3.99	4.11	0.00
ta019	20 x 10	14.90	6.58	9.81	14.34	13.16	6.58	0.87	0.00
ta020	20 x 10	8.87	6.14	1.10	6.14	3.94	4.06	0.75	0.00
ta021	20 x 20	10.88	7.19	2.30	4.27	4.56	3.94	3.08	0.00
ta022	20 x 20	13.89	0.79	9.11	9.11	13.27	3.50	0.09	0.00
ta023	20 x 20	6.43	0.63	1.09	1.54	4.59	10.56	0.00	8.01
ta024	20 x 20	23.36	8.28	12.49	18.01	19.28	7.49	6.84	0.00
ta025	20 x 20	5.98	2.15	1.85	3.24	4.92	3.62	0.00	8.75
ta026	20 x 20	15.73	4.54	8.39	11.95	12.89	3.18	2.42	0.00
ta027	20 x 20	7.00	2.53	1.45	4.77	4.23	2.49	4.14	0.00
ta028	20 x 20	2.23	0.00	1.90	2.27	2.23	5.62	3.93	3.35
AREP		15.14	5.20	4.78	7.69	7.70	5.06	2.21	**1.97**

CR: cognitive radio; MC: multi-criterion; HAMC: hybrid algorithm for multi-criterion; MGELS: modified gravitational emulation local search; AREP: average relative error percentage; HGASA: Hybrid genetic algorithm simulated annealing algorithm.

Table 4
Percentage improvement in total flow time value using HGASA over earlier literature results

Problem No	n x m	CR's [14]	CR (MC) [14]	HAMC1 [13]	HAMC2 [13]	HAMC3 [13]	D Tree [22]	MGELS [21]	HGASA
ta001	20 x 5	1.81	7.73	1.20	0.32	0.62	0.00	0.82	0.67
ta002	20 x 5	3.86	18.56	7.35	0.21	0.21	0.32	0.00	0.33
ta003	20 x 5	5.92	16.58	2.93	2.48	2.48	2.19	0.00	3.78
ta004	20 x 5	4.49	9.43	3.32	1.29	1.31	0.53	0.00	3.45
ta005	20 x 5	46.00	13.29	9.38	1.12	1.17	0.79	0.30	0.00
ta006	20 x 5	8.13	14.05	5.11	1.59	1.78	4.20	3.06	0.00
ta007	20 x 5	0.97	15.08	2.72	0.85	0.87	0.25	0.00	0.21
ta008	20 x 5	1.03	11.20	1.92	0.96	1.03	0.00	2.38	0.37
ta009	20 x 5	2.10	6.55	8.38	1.61	1.61	1.80	0.41	0.00
ta010	20 x 5	1.43	10.90	3.72	0.14	0.36	0.00	1.49	1.02
ta011	20 x 10	5.77	8.58	5.30	4.24	4.39	3.66	0.00	0.14
ta012	20 x 10	5.29	15.70	2.33	0.33	0.52	0.00	0.43	0.81
ta013	20 x 10	2.51	7.07	8.29	2.13	2.28	2.24	0.04	0.00
ta014	20 x 10	2.57	9.55	3.41	1.71	2.01	0.56	0.00	1.26
ta015	20 x 10	82.70	10.60	4.58	8.66	3.12	2.64	0.53	0.00
ta016	20 x 10	6.69	7.96	2.62	1.02	1.50	1.05	2.05	0.00
ta017	20 x 10	3.03	7.72	2.22	0.00	0.75	0.62	0.83	0.27
ta018	20 x 10	2.50	15.26	3.75	0.69	1.12	0.00	1.67	0.54
ta019	20 x 10	0.44	8.69	3.99	0.27	0.40	0.65	0.00	0.99
ta020	20 x 10	5.33	20.40	4.93	3.60	3.75	4.92	0.00	1.00
ta021	20 x 20	2.91	12.34	4.72	1.46	2.19	1.24	0.68	0.00
ta022	20 x 20	6.38	9.79	3.22	3.22	6.36	1.50	1.67	0.00
ta023	20 x 20	2.01	6.98	2.13	0.13	1.69	4.48	0.00	1.69
ta024	20 x 20	12.95	15.93	18.39	10.90	11.95	2.19	2.03	0.00
ta025	20 x 20	1.79	6.48	5.71	0.18	1.64	7.84	0.00	0.55
ta026	20 x 20	6.04	12.09	10.36	4.43	5.48	2.31	2.25	0.00
ta027	20 x 20	0.00	9.39	4.13	1.14	1.39	1.79	1.02	1.65
ta028	20 x 20	0.62	2.27	0.73	0.47	0.54	0.00	0.79	0.64
AREP		8.05	11.08	4.89	1.97	2.23	1.71	0.80	**0.69**

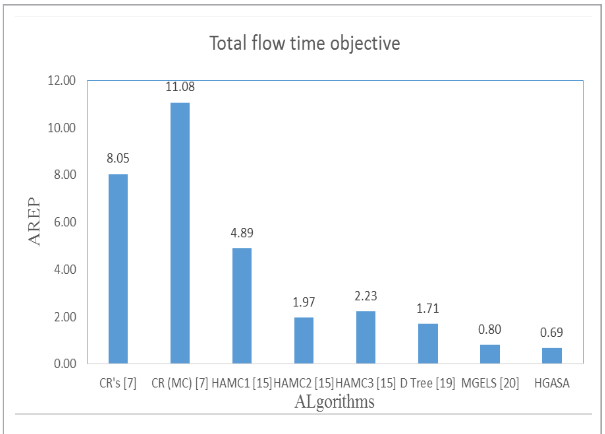
CR: cognitive radio; MC: multi-criterion; HAMC: hybrid algorithm for multi-criterion; MGELS: modified gravitational emulation local search; AREP: average relative error percentage; HGASA: Hybrid geneti c algorithm simulated annealing algorithm.

The performance of the algorithms is given using Average Relative Error Percentage (AREP) equation

$$AREP = (\frac{\min(solutions) - D^*}{D^*})x100\% \ , \tag{7}$$

where D^* is the Best flow time value.

Figure 4
A comparison of AREP of HGASA algorithm with other methods for Total flow time



5. Conclusion

In this work, HGASA based meta-heuristic approach is presented for bi-criteria optimization of minimizing makespan and total flow time simultaneously. It is a well-known combinatorial for permutation flow shop problem. The proposed algorithm is tested with 28 benchmark problems available in the literature and the results are compared. As a bi-criteria model, the proposed approach gives the best solution compared to the existing methods. Unlike the existing algorithms available for PFSP, to reach the global best solution, initially GA background is used to get a local best solution in the proposed algorithm. Later, the solution obtained through GA is given as input for SA algorithm, subjecting to neighborhood search by accepting some inferior count values to reach the global best solution. Measurable results of numerous problems of different sizes have demonstrated that the proposed technique meets or beats the other algorithms available in the literature. Progressive applications, more information and characteristics are gathered in shop floor control system and Hybrid Genetic Algorithm and Simulated Annealing algorithm will lead to better dispatching rules, while, it is difficult to evoke every single important part of the planning to alternate methodologies. The results of our performance measurement also revealed that the proposed HGASA algorithm outperformed the meta-heuristics in minimizing the makespan and total flow time.

In future, it could be added with more objectives such as machine idle time, total tardiness, total work load, and so on. Moreover, to solve permutation flow shop scheduling problems with other hybrid approaches is also more interesting. In addition, the HGASA algorithm could be applied to solve other combinatorial problems such as layout problems, job shop scheduling, flexible job shop scheduling and flexible manufacturing system scheduling problems.

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