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Two meta-heuristic algorithms for optimizing a multi-objective supply chain scheduling problem in an identical parallel machines environment

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▪ Appendix A: The pseudo-codes of algorithms

1. The pseudo-code explanation of the MOPSO algorithm

The pseudo-code of the MOPSO algorithm is as follows:

1. The initial population is generated randomly and a specific repository capacity should be created.
2. The value of each particle's objective functions in the population is computed.
3. The non-dominated members of the population are separated from the population and then stored in the repository.
4. In the search space, hypercubes are produced, each determining the particle coordinates according to the value of the particles' objective functions.
   The main loop of the algorithm
5. Get Repository by a selection mechanism such as Roulette Wheel Selection
6. Each particle from among the members of the repository chooses a leader and performs his own move.
7. The velocity of each particle and the best personal position are updated according to Eq. (A.1) and Eq. (A.2), respectively.

$$vel_i(t+1) = W \times vel_i(t) + C1\big(best.position_i(t) - position_i(t)\big) + C2(leader.position(t) - position_i(t)) \quad (A.1)$$

$$position_i(t+1) = position_i(t) + velocity_i(t+1) \quad (A.2)$$

   To compare the best position and a new position, the following should be performed:
   a. The new position will take the best position if dominating the best position.
   b. No action will be taken if the new position is dominated by the best position.
   c. One of the positions will be randomly considered as the best position If none dominates the other.
8. Apply Mutation with the probability of pm to create new particles.
9. The non-dominated members of the current population are added to the repository.
10. The dominated members of the repository are removed.
11. If the number of the repository members exceeds the capacity, additional members will be eliminated.
12. If the termination condition is not achieved, it will go to step 4 and otherwise, it ends.

2. The pseudo-code explanation of the NSGA-II

The pseudo-code of the NSGA-II is as follows:

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1. The initial population of chromosomes is randomly generated.
2. The objective function value is calculated for each chromosome within the population.
3. The population ranking is based on the following steps:
   3.1. The population ranking is performed according to the non-dominated sorting algorithm based on the definition and concept of dominance.
   3.2. The crowding distance is calculated according to Eq. (A.3) and a higher value is better; then the population is sorted descending.

$$d_i = \sum_{j=1}^{m} d_i^j \tag{A.3}$$

where d_i^j is calculated using Eq. (A.4):

$$d_i^j = \frac{|f_j^{i+1} - f_j^{i-1}|}{f_j^{max} - f_j^{min}} \tag{A.4}$$

4. A new set of the population is generated based on the repetition of the following steps:
   4.1. Parent selection:
      a. Two members of the population as the parent are randomly selected.
      b. If the rank of the two elected members is not the same, the winner will be a member with a lower rank.
      c. Otherwise, a member with more crowding distance is selected.
   4.2. The crossover operator is performed on parents to create new offspring.
   4.3. The mutation operator is performed randomly on chromosome genes to create mutated population.
5. The members of the new main population are selected from among the main population, offspring and mutated population using non-dominated sorting and crowding distance operations.
6. If the condition of the termination is not reached, it goes to step 2; otherwise, it goes to step 7.
7. The algorithm is terminated.

Appendix B: Comparing criteria

In this appendix, five comparing criteria are introduced to compare the solutions of the meta-heuristic algorithms.

1. The quality metric criterion *(QM)*

This metric is known as the most important criterion for comparing algorithms. This criterion is obtained in accordance with the following steps:

1. All Pareto solutions achieved from all algorithms are merged together.
2. The merged Pareto solutions are compared two by two, and dominated solutions are eliminated. Thus, a new set of Pareto solutions is generated.
3. The ratio of the number of Pareto solutions of each algorithm to the total number of Pareto solutions indicates the percentage of the quality metric for each algorithm.

The algorithm with a higher percentage of *QM* is better and has more efficient and effective solutions (Hassanzadeh et al., 2016).

2. The spacing metric criterion *(SM)*

The comparison metric is an important criterion and measures the monotony of the dispersion between non-dominated solutions. Eq. (B.1) defines this metric. A lower value of this criterion indicates better efficiency of the algorithm.

$$SM = \frac{\sum_{i=1}^{n-1}\left|\bar{d} - d_i\right|}{(n-1)\bar{d}} \tag{B.1}$$

where the Euclidean distance has to be calculated between consecutive solutions in the obtained set of Pareto solutions in order to obtain d_i, $\bar{d}$ is the mean value of d_i's and n is the total non-dominated solutions in the Pareto frontier (Attar et al., 2014; Piroozfard et al, 2018).

3. The mean ideal distance criterion *(MID)*

The *MID* is another important criterion, measuring the mean Euclidean distances of all Pareto-solutions from the ideal point for each algorithm. It could be determined with Eq. (B.2):

$$MID = \frac{\sum_{i=1}^{n}\sqrt{(f_{1,i} - f_1^{best})^2 + (f_{2,i} - f_2^{best})^2}}{n} \tag{B.2}$$

where f_{1i} and f_{2i} specify the i^{th} non-dominated solution fitness function values and f_1^{best} and f_2^{best} respectively define the best fitness function values for the first and second objective functions (ideal point). A lower value of this metric is appropriate (Piroozfard et al., 2018).

4. The diversification metric criterion *(DM)*

This comparison metric is calculated by using Eq. (B.3) to evaluate the extension of the frontiers in the generated non-dominated solutions, where l is the number of the objective functions and f_j is the j^{th} objective function value. A higher value of this criterion is better (Piroozfard et al., 2018).

$$DM = \sqrt{\sum_{j=1}^{l}(max(f_j) - min(f_j))^2} \tag{B.3}$$

5. The CPU time criterion *(CPUT)*

The processing time of achieving the Pareto curve for each algorithm is computed to determine the CPU time criterion. In other words, this metric shows the speed of each algorithm in solving the problem. A lower value of this criterion is better (Hassanzadeh et al., 2016).

▪ Appendix C: Resulting data of all experiments by meta-heuristic algorithms

Table C-1 Resulting data from solve the sample problems by NSGA-II for each class in small scale

Class A1_NSGA-II							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	2	8	0.103	951	94	2130	31
10		12	0.104	3825	96	7780	31
15		16	0.207	7363	80	16442	31
20		20	0.405	11104	98	24334	31
25		24	0.514	20006	92	45359	31
30	4	8	0.101	781	87	1525	36
35		12	0.311	1385	98	3425	33
40		16	0.404	3433	98	6880	32
45		20	0.301	7170	94	16329	31
50		24	0.502	8971	83	23163	31
55	6	8	0.101	609	61	923	34
60		12	0.404	1065	61	3017	33
65		16	0.506	1932	97	4829	33
70		20	0.404	2598	63	6444	32
75		24	0.613	4089	49	10807	32
Class A2_NSGA-II							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	2	8	0.101	1250	100	2462	33
10		12	0.202	3202	81	6710	32
15		16	0.402	6200	96	13675	32
20		20	0.301	9981	100	23459	31
25		24	0.524	18206	92	43147	31
30	4	8	0.505	871	93	1517	34
35		12	0.605	1520	94	3202	34
40		16	0.101	3410	95	8526	34
45		20	0.689	4136	67	12711	41
50		24	0.501	8719	57	20596	39
55	6	8	0.911	704	95	1266	35
60		12	0.706	1120	92	2459	37
65		16	0.401	2219	85	5237	37
70		20	0.101	3976	92	8527	36
75		24	0.302	4813	96	11539	36
Class A3_NSGA-II							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	2	8	0.101	1014	95	2623	33
10		12	0.305	3267	84	6116	34
15		16	0.611	5248	90	14893	33
20		20	0.203	11130	91	25433	33
25		24	0.611	21066	78	42332	33
30	4	8	0.101	1111	79	1975	34
35		12	0.107	1433	100	3072	34
40		16	0.404	3240	96	7830	33
45		20	0.814	3864	71	11043	33

50		24	0.652	6422	74	16792	32
55	6	8	0.614	751	46	1273	36
60		12	0.714	748	91	2727	35
65		16	0.506	2564	63	5821	34
70		20	0.302	2249	71	6851	34
75		24	0.403	4339	74	12119	33

Class B1_NSGA-II

Instance number	m	n	SM	MID	QM	DM	CPUT(S)
5	2	8	0.101	1177	99	2773	35
10		12	0.106	3951	97	8216	41
15		16	0.511	9704	100	19400	32
20		20	0.411	10814	89	26858	32
25		24	0.201	17939	99	42105	34
30	4	8	0.305	684	91	1233	36
35		12	0.512	1929	98	3742	33
40		16	0.401	2504	99	6469	35
45		20	0.812	4207	96	11684	34
50		24	0.401	10684	68	23156	32
55	6	8	0.201	705	61	1289	38
60		12	0.301	1273	97	2834	32
65		16	0.711	2681	94	5642	33
70		20	0.812	2837	75	7213	31
75		24	0.602	5199	86	12873	31

Class B2_NSGA-II

Instance number	m	n	SM	MID	QM	DM	CPUT(S)
5	2	8	0.101	821	100	1662	31
10		12	0.103	2655	92	5306	32
15		16	0.201	7043	87	14270	31
20		20	0.532	11898	96	26343	31
25		24	0.301	20769	92	48934	31
30	4	8	0.101	642	26	1082	34
35		12	0.303	1112	76	3675	33
40		16	0.409	2351	96	6064	32
45		20	0.610	4317	98	11442	32
50		24	0.210	8189	94	20261	31
55	6	8	0.101	555	89	1011	34
60		12	0.107	1201	85	2658	34
65		16	0.131	2112	88	4971	33
70		20	0.155	2837	90	8459	32
75		24	0.132	4300	85	10239	33

Class B3_NSGA-II

Instance number	m	n	SM	MID	QM	DM	CPUT(S)
5	2	8	0.101	539	97	1059	34
10		12	0.102	2608	84	5695	33
15		16	0.303	5455	100	12829	32
20		20	0.808	9949	83	28603	32
25		24	0.304	13739	89	32850	32
30	4	8	0.101	1269	95	1786	53
35		12	0.403	1179	99	2762	34
40		16	0.713	2304	91	6945	33

45		20	0.511	3846	93	12600	32
50		24	0.611	6360	91	18022	32
55	6	8	0.202	1016	91	1352	34
60		12	0.511	963	81	2897	34
65		16	0.814	2061	94	5569	33
70		20	0.351	2443	96	6438	34
75		24	0.404	3805	95	10907	33

Class C1_NSGA-II

Instance number	m	n	SM	MID	QM	DM	CPUT(S)
5	2	8	0.101	1107	85	2677	33
10		12	0.123	2870	96	5381	32
15		16	0.452	6181	100	16674	31
20		20	0.707	13292	87	32378	33
25		24	0.151	23765	99	48308	32
30	4	8	0.409	737	72	1302	34
35		12	0.203	1442	98	2956	33
40		16	0.507	2872	92	6813	32
45		20	0.311	5778	83	12600	31
50		24	0.310	9167	86	21468	31
55	6	8	0.101	861	61	1490	33
60		12	0.511	1371	86	2995	33
65		16	0.210	2694	90	5934	33
70		20	0.303	2798	71	7553	33
75		24	0.101	4930	79	12979	32

Class C2_NSGA-II

Instance number	m	n	SM	MID	QM	DM	CPUT(S)
5	2	8	0.101	1492	99	2900	33
10		12	0.511	4539	73	7563	34
15		16	0.407	8498	100	18056	32
20		20	0.201	15481	88	37184	32
25		24	0.604	20658	96	51487	32
30	4	8	0.101	603	68	1414	34
35		12	0.305	1270	96	3248	34
40		16	0.101	2970	94	6761	33
45		20	0.104	4927	95	12461	33
50		24	0.303	7572	90	20818	32
55	6	8	0.101	556	95	1045	34
60		12	0.105	1213	95	3133	34
65		16	0.145	1817	97	4751	33
70		20	0.167	3095	72	8558	33
75		24	0.135	5229	95	13840	36

Class C3_NSGA-II

Instance number	m	n	SM	MID	QM	DM	CPUT(S)
5	2	8	0.101	1317	99	2693	35
10		12	0.102	3258	100	5783	34
15		16	0.305	4788	99	14744	34
20		20	0.412	9116	99	23000	34
25		24	0.306	15997	97	34013	33
30	4	8	0.101	1048	100	1647	34
35		12	0.411	1273	98	3399	35

40		16	0.105	2449	59	6640	34
45		20	0.307	4471	88	10810	34
50		24	0.508	6168	37	15193	35
55	6	8	0.101	752	39	1076	35
60		12	0.115	1384	95	2543	33
65		16	0.202	1755	99	5031	34
70		20	0.410	3104	96	8341	33
75		24	0.208	3756	84	11257	33

Table C-2 Resulting data from solve the sample problems by MOPSO for each class in small scale

Class A1_MOPSO							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	2	8	0.811	2308	6	4260	6
10		12	0.630	3760	4	8530	6
15		16	0.764	4593	20	9298	7
20		20	0.441	9666	2	20331	6
25		24	0.656	10228	8	22958	6
30	4	8	1.274	1481	13	4481	7
35		12	1.452	3201	2	7489	5
40		16	1.459	5450	2	13689	5
45		20	0.789	7561	6	18637	6
50		24	0.666	6249	17	16860	6
55	6	8	0.429	912	39	2804	6
60		12	0.538	704	39	2551	8
65		16	1.197	2791	3	8143	6
70		20	0.623	2487	37	7489	6
75		24	0.453	2674	51	8670	7
Class A2_MOPSO							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	2	8	1.138	2817	0	6054	5
10		12	0.334	2749	19	5291	8
15		16	1.185	8613	4	18964	5
20		20	1.016	11479	0	24179	5
25		24	0.991	11297	8	24715	6
30	4	8	0.923	1325	7	3411	5
35		12	0.773	2134	6	5746	6
40		16	1.417	4419	5	12420	5
45		20	0.628	2755	33	7863	6
50		24	0.814	10610	43	29880	6
55	6	8	1.393	1339	5	3599	5
60		12	0.939	1770	8	5439	6
65		16	1.202	2298	15	7171	6
70		20	0.956	6151	8	18324	6
75		24	1.115	6657	4	19724	13
Class A3_MOPSO							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	2	8	0.281	3117	5	6042	7
10		12	0.715	5622	16	13097	6
15		16	0.878	7328	10	16026	7

20		20	0.590	8859	9	19455	6
25		24	0.418	8596	22	20042	7
30	4	8	1.212	991	21	2588	6
35		12	1.475	2467	0	6252	5
40		16	0.704	3482	4	9155	6
45		20	0.721	4424	29	13172	7
50		24	0.495	4384	26	10945	7
55	6	8	0.438	417	54	1428	8
60		12	0.607	1702	9	4522	5
65		16	0.772	1491	37	4600	8
70		20	0.349	2190	29	6410	7
75		24	0.597	4288	26	12826	7

Class B1_MOPSO

Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	2	8	0.693	2936	1	5832	6
10		12	0.671	3989	3	9623	8
15		16	1.445	7138	0	16220	5
20		20	0.515	7438	11	17614	7
25		24	0.347	15722	1	31878	6
30	4	8	0.786	944	9	2608	7
35		12	0.947	1912	2	5256	5
40		16	1.076	4254	1	11451	6
45		20	1.123	7279	4	17890	5
50		24	0.366	4905	32	15057	7
55	6	8	0.288	658	39	2587	15
60		12	1.064	2050	3	5524	5
65		16	0.888	4381	6	12154	5
70		20	0.794	3031	25	8508	6
75		24	0.751	5501	14	13083	6

Class B2_MOPSO

Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	2	8	0.643	2351	0	4675	7
10		12	0.406	2358	8	5681	9
15		16	0.641	4206	13	10666	7
20		20	0.745	10398	4	23197	6
25		24	0.564	11754	8	27318	6
30	4	8	0.216	199	74	464	9
35		12	0.401	1263	24	3853	7
40		16	1.017	2627	4	6929	6
45		20	0.928	4871	2	13454	6
50		24	0.490	7177	6	16973	6
55	6	8	0.431	743	11	2293	6
60		12	1.156	1654	15	5087	6
65		16	0.886	2034	12	5573	5
70		20	0.649	3971	10	11638	6
75		24	1.067	4990	15	13894	6

Class B3_MOPSO

Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	2	8	1.220	1765	3	3196	8
10		12	0.421	6028	16	13547	6

15		16	1.109	7474	0	15970	5
20		20	0.586	7881	17	18782	7
25		24	0.367	10286	11	23079	7
30	4	8	1.033	938	5	2445	12
35		12	1.263	2339	1	6768	5
40		16	0.777	2844	9	7000	6
45		20	1.661	4222	7	11054	6
50		24	0.631	5828	9	16572	6
55	6	8	0.912	742	9	2170	6
60		12	0.683	1829	19	6495	6
65		16	1.001	2730	6	8191	5
70		20	0.805	4207	4	11944	5
75		24	1.215	4562	5	12036	6
Class C1_MOPSO							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	2	8	0.394	3112	15	7234	8
10		12	1.102	4970	4	9845	5
15		16	1.583	8655	0	19151	5
20		20	0.275	10814	13	25629	7
25		24	1.550	16101	1	31750	6
30	4	8	0.437	688	28	2044	7
35		12	0.638	2971	2	7458	5
40		16	0.906	3949	8	10557	6
45		20	0.548	4566	17	12844	6
50		24	0.979	8961	14	22641	6
55	6	8	0.414	942	39	3463	8
60		12	0.789	1772	14	4550	6
65		16	0.876	3363	10	9728	6
70		20	0.328	2620	29	8419	7
75		24	0.552	4114	21	13359	7
Class C2_MOPSO							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	2	8	1.480	2455	1	4787	5
10		12	0.394	3102	27	5943	8
15		16	1.512	7268	0	15339	5
20		20	0.544	12166	12	25003	6
25		24	0.892	11322	4	23079	6
30	4	8	0.466	930	32	2825	7
35		12	1.106	1888	4	4819	6
40		16	0.714	3478	6	10417	5
45		20	1.574	6008	5	16667	6
50		24	0.754	6950	10	18176	6
55	6	8	0.868	836	5	2583	5
60		12	0.733	1694	5	4713	5
65		16	1.749	4512	3	11759	6
70		20	1.043	2827	28	7968	6
75		24	0.967	6275	5	15434	6
Class C3_MOPSO							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	2	8	0.859	2298	1	4453	5

10		12	1.129	5552	0	11901	5
15		16	1.195	6489	1	14689	5
20		20	1.349	11682	1	26620	5
25		24	1.216	12235	3	24727	6
30	4	8	0.716	1170	0	3162	5
35		12	1.135	1891	2	4132	5
40		16	0.689	2285	41	6052	7
45		20	1.141	4798	12	12208	6
50		24	0.428	2769	63	8858	8
55	6	8	0.347	579	61	1820	7
60		12	0.867	1255	5	3641	6
65		16	1.512	2615	1	6593	5
70		20	1.684	4096	4	10372	6
75		24	1.322	4571	16	13027	6

Table C-3 Resulting data from solve the sample problems by NSGA-II and MOPSO for each class in medium and large scale

Class A1_NSGA-II							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	8	40	0.287	8441	70	28366	231
10		80	0.299	38502	59	138682	240
15		120	0.315	89161	52	384894	241
20		180	0.429	228167	41	1259497	236
25		250	0.274	984662	75	2873300	238
30	16	40	0.287	3339	95	16481	226
35		80	0.627	18367	78	64226	225
40		120	0.297	47630	46	148555	229
45		180	0.383	114558	31	416297	262
50		250	0.477	219594	51	825240	269
55	27	40	0.292	5486	93	12501	243
60		80	0.488	7499	98	31741	256
65		120	0.293	20318	63	90345	259
70		180	0.393	80331	39	194553	260
75		250	0.540	99191	45	364785	269
Class A2_NSGA-II							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	8	40	0.511	8770	91	29622	242
10		80	0.317	44061	44	139173	228
15		120	0.357	103251	43	398967	241
20		180	0.478	285813	34	1205210	246
25		250	0.593	1059021	52	2812182	254
30	16	40	0.438	5600	91	15873	180
35		80	0.308	16524	59	69495	183
40		120	0.523	53245	82	158594	183
45		180	0.554	90935	52	376420	190
50		250	0.721	294637	56	778600	195
55	27	40	0.307	5223	100	12795	185
60		80	0.463	9450	72	37010	183
65		120	0.409	19496	61	85481	187
70		180	0.341	85144	30	216767	191

75		250	0.449	97100	19	396911	252

Class A3_NSGA-II

Instance number	m	n	SM	MID	QM	DM	CPUT(S)
5	8	40	0.317	6558	71	25938	229
10		80	0.417	25991	43	129413	231
15		120	0.714	150475	67	417303	227
20		180	0.912	471051	42	1163942	238
25		250	0.810	1167410	20	2634241	243
30	16	40	0.403	5820	95	17146	238
35		80	0.287	18710	31	55803	233
40		120	0.454	45312	78	147709	248
45		180	0.304	101673	12	348079	255
50		250	0.371	211242	78	859149	256
55	27	40	0.581	5067	98	13890	237
60		80	0.287	4649	94	30624	239
65		120	0.343	16184	62	74513	195
70		180	0.306	64755	30	182861	192
75		250	0.432	128288	33	355610	201

Class B1_NSGA-II

Instance number	m	n	SM	MID	QM	DM	CPUT(S)
5	8	40	0.287	9138	73	32591	177
10		80	0.354	47477	67	157265	175
15		120	0.389	124677	34	412507	178
20		180	0.495	334189	38	1027486	183
25		250	0.840	972784	69	2930873	189
30	16	40	0.525	3801	98	16943	180
35		80	0.314	17824	86	63738	180
40		120	0.378	35943	12	155835	180
45		180	0.295	150329	41	358567	187
50		250	0.576	291994	77	812355	191
55	27	40	0.301	7076	100	15532	181
60		80	0.352	13505	88	41262	190
65		120	0.297	35834	54	93295	192
70		180	0.376	52750	83	197983	199
75		250	0.714	123434	78	385039	205

Class B2_NSGA-II

Instance number	m	n	SM	MID	QM	DM	CPUT(S)
5	8	40	0.398	10536	51	32621	193
10		80	0.471	37191	51	138704	191
15		120	0.552	142894	11	437061	193
20		180	0.664	442982	65	1204119	199
25		250	0.431	703542	69	2647128	207
30	16	40	0.334	3293	72	14098	195
35		80	0.410	20034	63	63563	195
40		120	0.293	38092	35	168569	198
45		180	0.345	93794	60	371699	203
50		250	0.569	242824	51	864417	208
55	27	40	0.297	6717	100	16071	192
60		80	0.329	7297	96	39911	199
65		120	0.291	19598	92	90677	198

70		180	0.324	53323	43	208853	207
75		250	0.336	97047	32	361854	212
Class B3_NSGA-II							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	8	40	0.287	8094	93	27937	193
10		80	0.287	37264	32	149799	192
15		120	0.360	117455	6	390923	194
20		180	0.661	406048	17	1168608	196
25		250	0.983	821051	67	2683657	201
30	16	40	0.307	7105	87	18012	190
35		80	0.362	10307	42	48522	194
40		120	0.456	43339	18	141637	196
45		180	0.364	100611	70	396384	198
50		250	0.437	227091	27	830842	203
55	27	40	0.366	5396	98	13075	192
60		80	0.297	8620	87	37027	196
65		120	0.391	23775	97	77254	197
70		180	0.485	48216	25	179144	201
75		250	0.381	102847	59	367585	214
Class C1_NSGA-II							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	8	40	0.287	9935	99	28820	191
10		80	0.322	37628	34	146542	194
15		120	0.363	154311	60	411559	195
20		180	0.808	401397	66	1088696	201
25		250	0.668	941896	45	2682408	205
30	16	40	0.457	5964	100	18151	192
35		80	0.288	13891	83	67240	193
40		120	0.287	42680	69	154843	188
45		180	0.581	127511	52	410323	193
50		250	0.372	176231	48	878161	201
55	27	40	0.287	3648	100	13978	190
60		80	0.543	10691	96	40332	192
65		120	0.495	29769	66	104318	191
70		180	0.313	69294	56	192690	199
75		250	0.287	130301	33	418975	204
Class C2_NSGA-II							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	8	40	0.415	8760	97	29007	177
10		80	0.384	42610	67	159058	177
15		120	0.607	91323	45	422311	182
20		180	0.710	457436	52	1069973	186
25		250	0.433	1124125	57	2718487	191
30	16	40	0.515	4399	72	17621	180
35		80	0.551	16466	62	71099	181
40		120	0.363	37476	71	149799	182
45		180	0.370	69228	24	369178	195
50		250	0.744	292210	56	803364	201
55	27	40	0.306	7744	97	15917	185
60		80	0.347	8786	95	41248	189

Instance number	m	n	SM	MID	QM	DM	CPUT(S)
65		120	0.400	21085	86	97926	192
70		180	0.494	56103	19	209529	195
75		250	0.499	112525	56	413402	203
Class C3_NSGA-II							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	8	40	0.329	8426	100	29390	189
10		80	0.344	27788	30	148909	187
15		120	0.453	102901	67	401134	189
20		180	0.328	335331	67	1112200	194
25		250	0.828	1031339	79	2867639	199
30	16	40	0.435	5852	100	15871	188
35		80	0.417	17924	71	63183	192
40		120	0.320	39664	22	150233	191
45		180	0.570	77704	20	341920	197
50		250	0.414	266450	57	819883	203
55	27	40	0.287	4611	100	15807	190
60		80	0.293	10613	97	41020	193
65		120	0.350	16597	38	83148	192
70		180	0.429	49430	63	192167	199
75		250	0.536	119244	49	392843	202
Class A1_MOPSO							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	8	40	0.534	10165	30	30229	19
10		80	0.500	55938	41	142336	28
15		120	0.522	117801	48	282380	35
20		180	0.767	256901	59	675032	49
25		250	0.376	711431	25	1532318	65
30	16	40	0.898	7576	5	20085	19
35		80	0.891	32251	22	79218	26
40		120	0.595	77380	54	178929	36
45		180	0.538	172707	69	443154	57
50		250	0.402	342772	49	796654	70
55	27	40	0.695	6270	7	16583	29
60		80	0.612	20210	2	50465	36
65		120	0.550	44174	37	110012	43
70		180	0.547	103510	61	242866	54
75		250	0.541	236651	55	523180	73
Class A2_MOPSO							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	8	40	0.816	18933	9	50073	19
10		80	0.574	70655	56	156695	28
15		120	0.517	118112	57	279888	38
20		180	0.401	354015	66	779665	52
25		250	0.634	793976	48	1632901	69
30	16	40	0.723	8237	9	19310	15
35		80	0.517	38215	41	93289	21
40		120	1.044	63626	18	156644	27
45		180	0.394	180837	48	431941	38
50		250	0.490	364083	44	830085	52
55	27	40	0.888	6354	0	13888	18

60		80	0.805	13329	28	29996	23
65		120	0.433	43361	39	105234	29
70		180	0.498	117166	70	280072	40
75		250	0.493	241180	81	539073	70

Class A3_MOPSO

Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	8	40	0.704	7962	29	21411	19
10		80	0.713	23439	57	65765	26
15		120	1.302	110842	33	278813	35
20		180	0.721	262580	58	730404	50
25		250	0.418	400884	80	964041	66
30	16	40	1.229	8408	5	22655	20
35		80	1.061	13168	69	36307	29
40		120	1.422	61989	22	127907	38
45		180	0.658	160354	88	404456	51
50		250	0.902	261716	22	582441	70
55	27	40	0.766	5481	2	13284	25
60		80	0.784	20247	6	46723	33
65		120	0.762	40146	38	96383	40
70		180	0.771	83236	70	182566	40
75		250	0.492	155917	67	362893	54

Class B1_MOPSO

Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	8	40	0.841	14378	27	35749	13
10		80	0.622	83945	33	215793	20
15		120	0.335	118736	66	288067	27
20		180	0.584	310698	62	771908	37
25		250	0.335	597654	31	1428455	50
30	16	40	0.586	10929	2	26825	15
35		80	0.588	55470	14	128248	21
40		120	0.548	49809	88	129777	28
45		180	0.351	234201	59	562768	39
50		250	0.442	295996	23	671467	51
55	27	40	0.878	6586	0	16941	18
60		80	0.632	25121	12	62467	22
65		120	0.769	50594	46	124320	29
70		180	0.779	129753	17	309416	40
75		250	0.363	241126	22	540418	54

Class B2_MOPSO

Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	8	40	0.555	7609	49	21623	15
10		80	0.428	51311	49	128368	20
15		120	0.288	165370	89	428515	27
20		180	0.495	322808	35	743165	39
25		250	0.726	502362	31	1198180	52
30	16	40	0.966	6746	28	20770	17
35		80	1.256	24608	37	59234	21
40		120	0.475	94213	65	224799	29
45		180	0.507	176392	40	406764	40
50		250	0.426	329620	49	753573	53

55	27	40	0.576	6230	0	16216	18
60		80	0.535	19398	4	44332	22
65		120	0.566	52771	8	126857	30
70		180	0.318	99647	57	253806	41
75		250	0.627	213482	68	502005	55

Class B3_MOPSO

Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	8	40	1.091	16256	7	40261	14
10		80	0.846	79075	68	205788	20
15		120	0.407	94660	94	243800	26
20		180	0.538	342109	83	835040	37
25		250	0.940	260923	33	683467	50
30	16	40	0.548	6281	13	15776	15
35		80	0.739	22678	58	54222	21
40		120	0.837	96449	82	255791	28
45		180	1.022	169272	30	378312	38
50		250	0.671	404816	73	1001010	51
55	27	40	0.854	7567	2	18201	18
60		80	0.948	17842	13	44806	22
65		120	0.977	42738	3	96519	29
70		180	0.542	114213	75	296035	40
75		250	0.573	219041	41	511597	56

Class C1_MOPSO

Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	8	40	1.058	20052	1	47284	14
10		80	0.634	62842	66	153696	21
15		120	0.668	120682	40	309246	28
20		180	0.337	386358	34	911282	38
25		250	0.398	764275	55	1740520	52
30	16	40	0.831	10632	0	22887	15
35		80	0.410	46038	17	112956	22
40		120	0.594	75374	31	195698	28
45		180	0.358	172117	48	384213	38
50		250	0.617	364624	52	847906	51
55	27	40	0.932	7230	0	17312	18
60		80	1.070	23964	4	60869	22
65		120	0.423	61123	34	144013	29
70		180	0.400	116724	44	270206	40
75		250	0.318	244111	67	570885	54

Class C2_MOPSO

Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	8	40	0.530	20575	3	48522	13
10		80	0.496	67629	33	161480	20
15		120	0.484	202711	55	457054	27
20		180	0.601	305720	48	771059	37
25		250	0.309	774433	43	1697965	50
30	16	40	0.991	5542	28	13876	16
35		80	0.544	30437	38	75834	21
40		120	0.713	92829	29	214239	28
45		180	0.370	181437	76	388619	42

50		250	0.420	391482	44	869736	53
55	27	40	0.711	5104	3	12262	18
60		80	0.674	28694	5	68160	23
65		120	0.728	47961	14	108010	30
70		180	0.357	101734	81	239986	41
75		250	0.424	214909	44	488751	55
Class C3_MOPSO							
Instance number	**m**	**n**	**SM**	**MID**	**QM**	**DM**	**CPUT(S)**
5	8	40	1.240	17108	0	40275	13
10		80	0.388	53060	70	142585	20
15		120	1.318	116321	33	290618	27
20		180	0.451	269576	33	624495	37
25		250	0.717	382139	21	907898	51
30	16	40	1.270	8664	0	19203	15
35		80	0.685	32685	29	74392	21
40		120	0.617	93087	78	211973	28
45		180	1.072	159617	80	404915	39
50		250	0.586	283732	43	624026	52
55	27	40	1.112	5924	0	15010	18
60		80	0.586	24649	3	57041	22
65		120	1.099	59268	62	136845	30
70		180	0.932	106289	37	263034	41
75		250	0.707	232894	51	538257	56

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