Evolutionary Multi/Many-Objective Approaches for Next Release Optimization Problem

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Introduction

- We have developed a novel Evolutionary algorithms to deal with Many-objective problem
- We have also developed a novel mutation strategies for Next Release problem

Hierarchical Approaches for Many-objective-optimization

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Introduction

- Pareto-dominance multi-objective evolutionary algorithms (PDMOEAs) are extensively employed in the literature to handle multi-objective problems (MOPs) effectively.

- However, the performance of PDMOEAs drastically reduces for the problems with higher objectives termed as the many-objective problems (MaOPs) due to the inefficiency of the Pareto-dominance to segregate the solutions.

- Hence, in this work, we propose a hierarchical approach for the PDMOEAs to solve the MaOPs.

- The proposed approach employs Pareto-dominance along with approximate nondominated sorting and Shift-based density estimation in the mating and environmental selections to select and preserve better solutions respectively.

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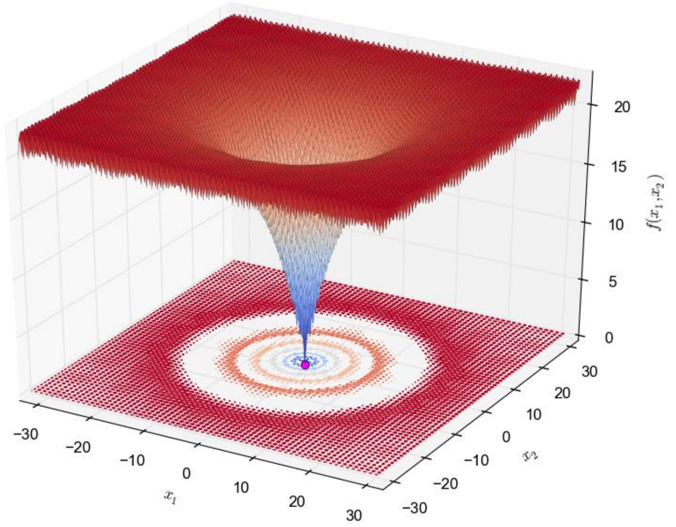
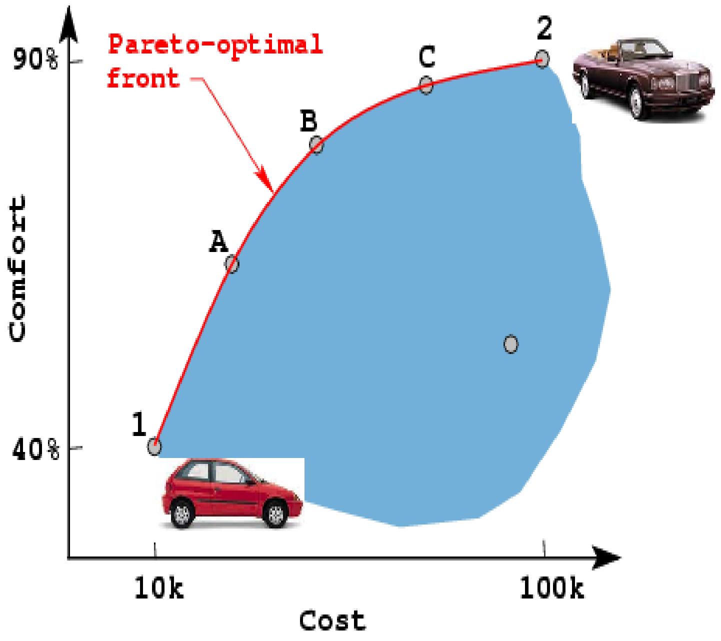
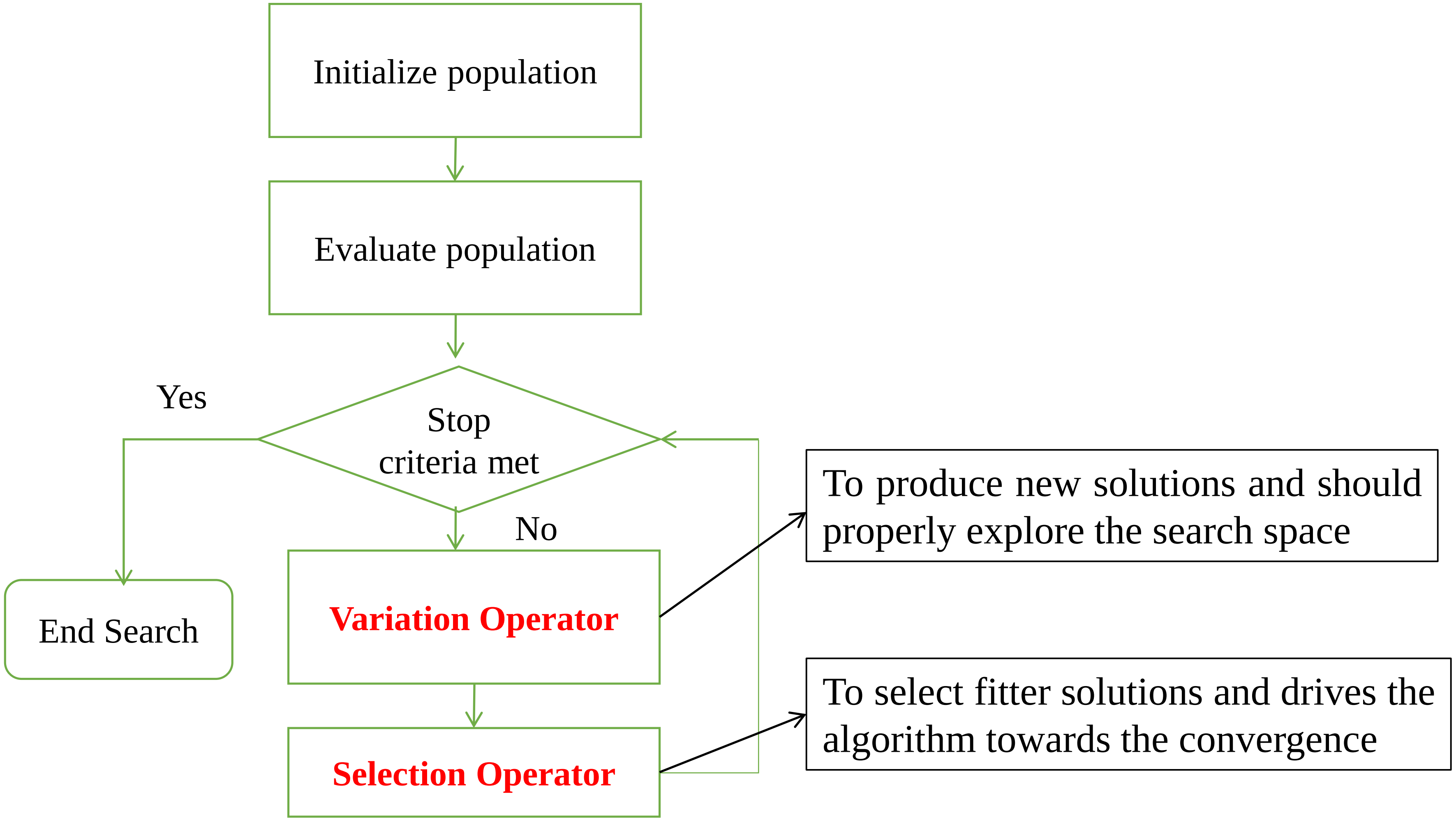
Basic of Multi/Many-objective

Single-objective Optimization Problems	Multi-objective Optimization Problems
$Minimize\ f(x)$ subject to $x \in \Omega$	$Minimize\ F(x) = (f_1(x), f_2(x), \dots, f_m(x))$ subject to $x \in \Omega$





General Framework of Evolutionary Algorithm



Approaches to Solve Multi-Objective Optimization

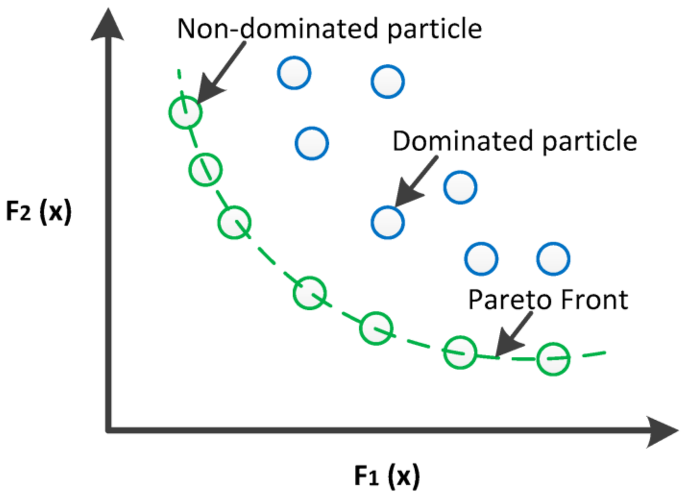
Pareto-Dominance based Approach	Indicator-based Approach	Decomposition-based Approach

Approaches to Solve Multi-Objective Optimization

Pareto-Dominance based Approach	Indicator-based Approach	Decomposition-based Approach

- **Pareto dominance based approach means the qualities of the candidate solutions are compared using Pareto Rank (Nondominated sorting) .**

- Nondominated sorting is a procedure where **solutions in the population are assigned to different fronts** based on their dominance relationships



Minimization

Case I:
A dominates B

Solutions	Obj1	Obj2	Obj3	Obj4
A	0.6	0.5	0.7	0.3
B	0.7	0.75	0.85	0.55

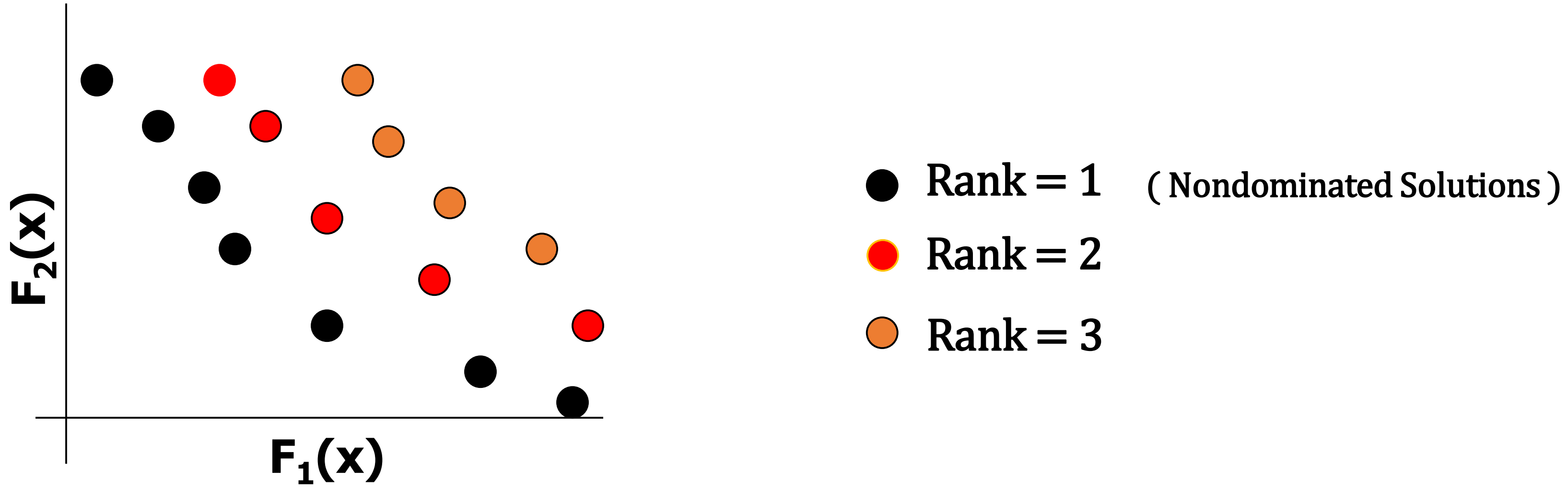
Case II:
A and B are nondominated

Solutions	Obj1	Obj2	Obj3	Obj4
A	0.6	0.5	0.7	0.3
B	0.5	0.75	0.65	0.55

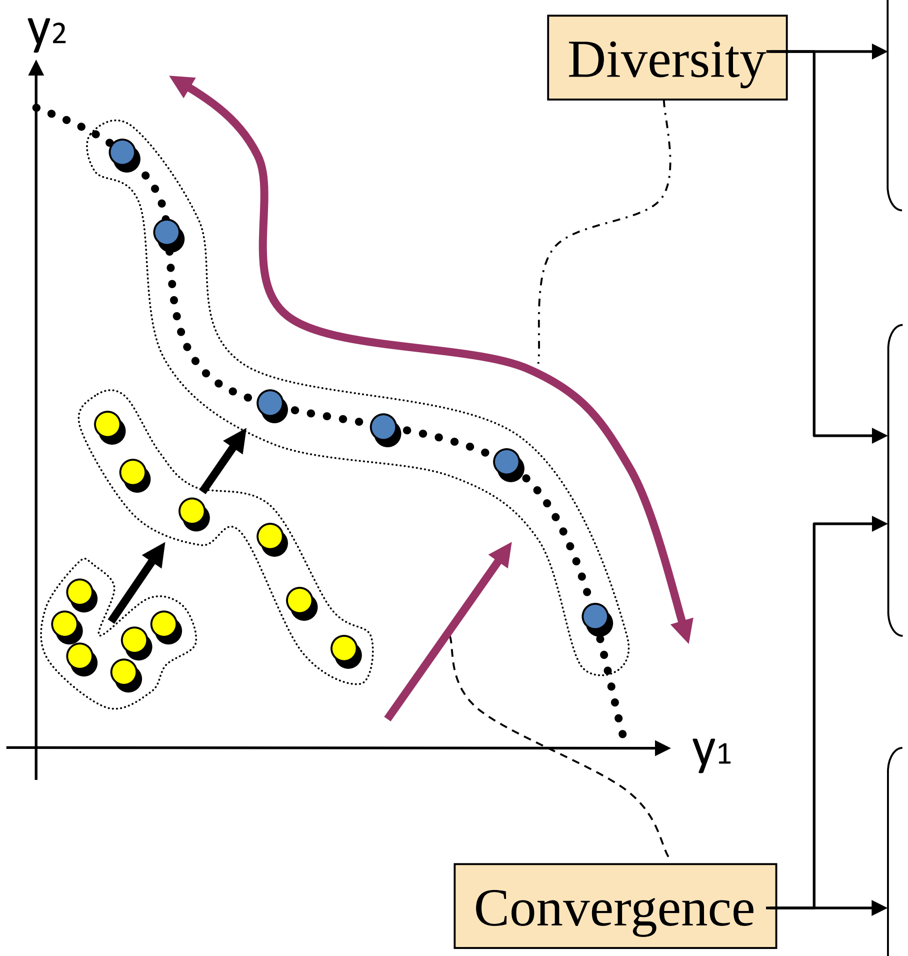
Approaches to Solve Multi-Objective Optimization

Pareto-Dominance based Approach	Indicator-based Approach	Decomposition-based Approach

Concept Behind Pareto-Dominance



Issues in Multi-objective Optimization



- How to maintain a diverse Pareto set approximation?

  ❷ **density estimation**

- How to prevent nondominated solutions from being lost?

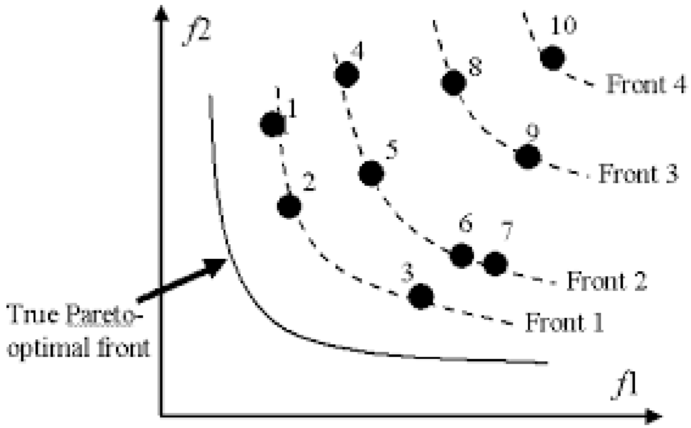
  ❸ **environmental selection**

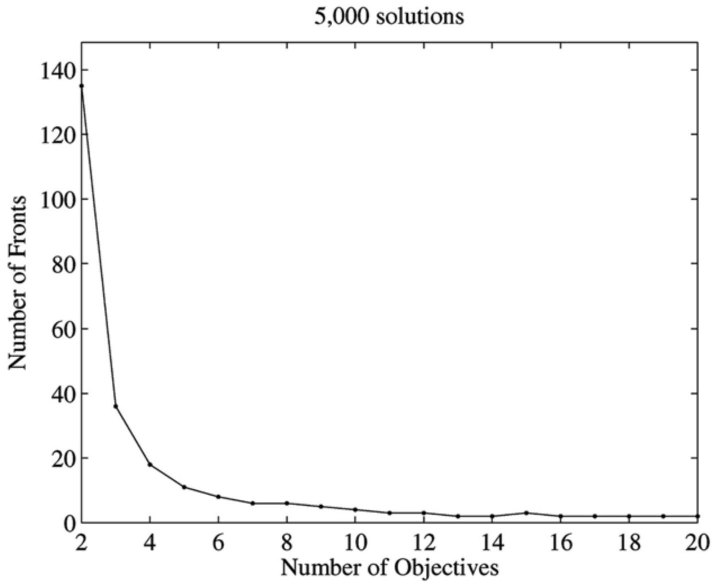
- How to guide the population towards the Pareto set?

  ❶ **fitness assignment**

Many-objective optimization & Its problems

- Multi-objective problems (MOPs) with the number of objectives more than three, are often known as Many-objective optimization problems (MaOPs).
- As the number of objectives increases, the effect of Pareto-Dominance vanishes gradually, which in turn effects the diversity and convergence..
- To achieve the better convergence and diversity, there is necessity to adopt an additional secondary selection criterion.





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Proposed Method

- We utilize the advantages provided by the AENS approach and shift-based density estimation to improve the performance of PDMOEAs in handling the MaOPs.

- The proposed approach aims at balancing both the convergence and diversity.

- We propose a hierarchical approach for the PDMOEAs to solve the MaOPs.

- The proposed approach employs Pareto-dominance along with approximate nondominated sorting and Shift-based density estimation in the mating and environmental selections to select and preserve better solutions respectively.

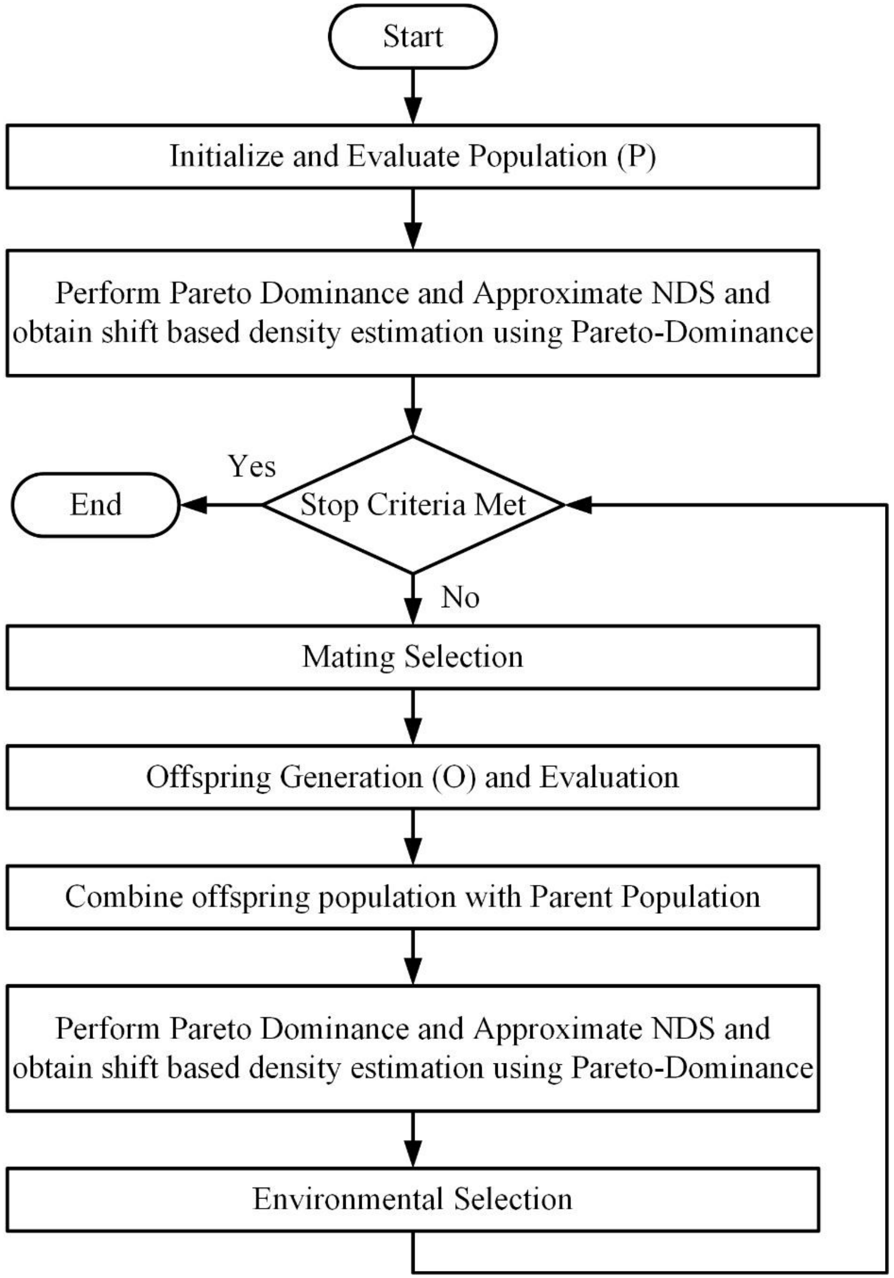
General Framework of the Proposed Method

- In the proposed hierarchical approach, at first, parent population P_1 of size N is random initialized and evaluated.

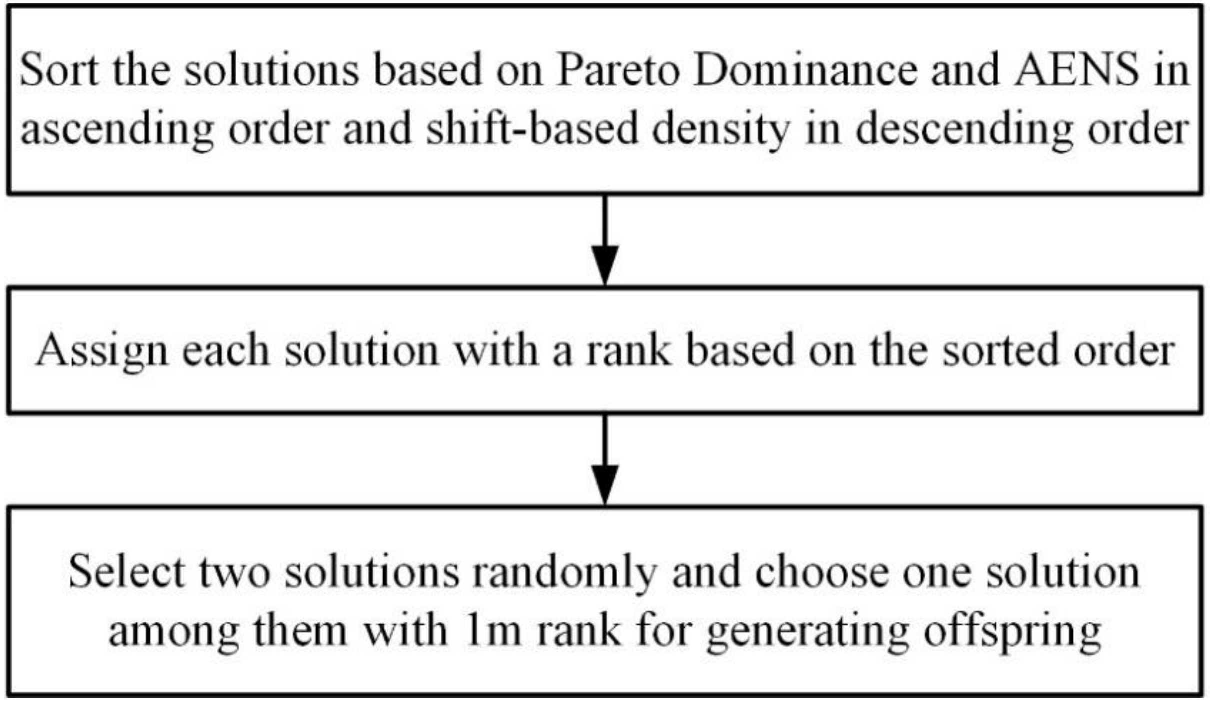
- After Initialization, mating section procedure is adopted to generate offspring and the parents are selected based on the sorted order of the Pareto-dominance, AENS and shift-based density estimation.

- After the mating selection, the obtained offspring population is combined with the parent population and the Pareto-dominance, AENS approach and shift-based density procedures are employed.

- Then environmental selection procedure is adopted to preserve the elite solutions for the next generations.



Mating Selection

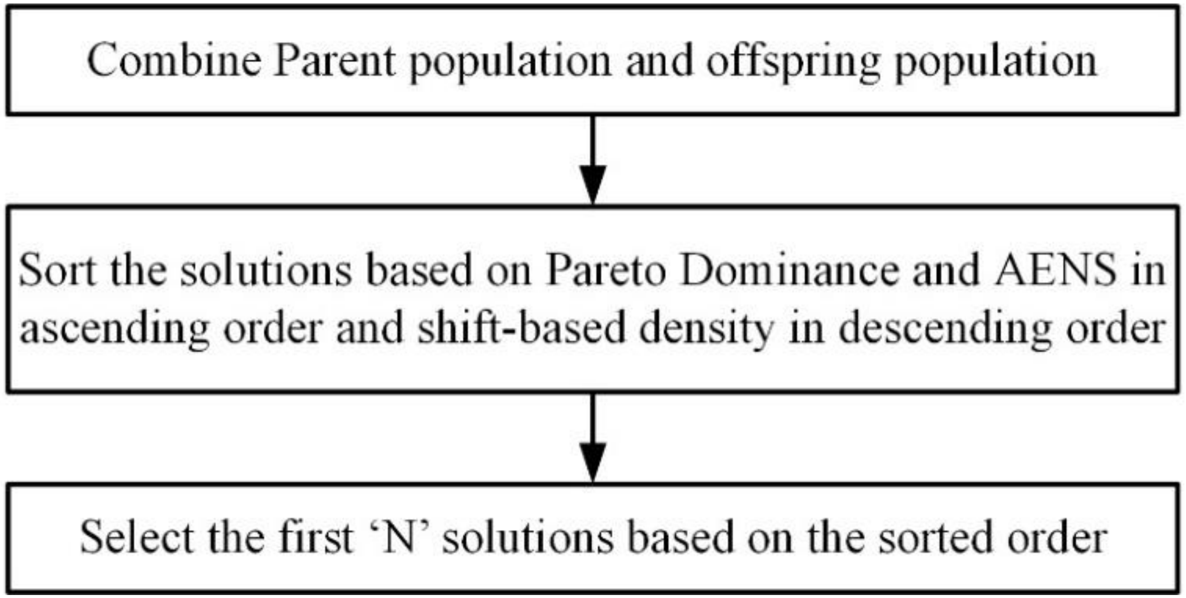


- After the Pareto-dominance, for solutions in each nondominated fronts, AENS approach is adopted. In other words, each solution will be assigned with Pareto rank based on Pareto-dominance and sub-Pareto rank based on AENS approach.

- For each solution, shift-based density estimation is obtained with the help of the Pareto-dominance. Each solution is sorted based on Par eto rank and sub-Pareto rank in ascending order and shift-based density estimation in descending order. Then for each solution a rank is assigned based on the sorted order.

- After obtaining the rank, randomly two individu als are selected. Both the solutions will be comp ared based on the rank and the solution with less rank is selected for the offspring generation. If b oth the solutions A and B have rank, then one so lution is chosen is random.

Environmental Selection



- In the environmental selection, Pareto-dominance procedure is adopted on the combined parent and offspring population. Then similar to the mating selection, sub-Pareto rank and shift-based density for each solution are obtained.

- As mentioned in the mating selection, the solutions are sorted based on the Pareto rank and sub-Pareto rank in ascending order and shift-based density estimation in descending order and the best N solutions are chosen in the sorted order

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Experimental Setup

- We have conducted experiments on two popular benchmark test suites DTLZ and WFG
- The DTLZ test suite consists of seven problems DTLZ1 to DTLZ7 and WFG test suite contains of nine problems WFG1 to WFG9
- To demonstrate the effectiveness of the proposed hierarchical approach, we have compared our method with state-of-art algorithms such as NSGA-II, SPEA2, KnEA, and NSGA-III.
- To compare the performance of the proposed approach with the state-of-art algorithms, we have employed the hypervolume (HV) indicator. The hypervolume indicator considers both convergence and diversity.
- The algorithm with higher value of hypervolume is considered as best performing algorithm

Results

Table1: Mean and Standard Deviation of Hypervolume results for DTLZ problems

Problem	M	NSGA-II			SPEA2			KnEA			NSGAIII			Hierarchical	
DTLZ1	4	0.7913	0.2412	(+)	0.9103	0.0010	(–)	0.6415	0.1294	(+)	0.9120	0.0005	(–)	0.8589	0.0214
	6	0.1346	0.2611	(+)	0.8193	0.2822	(+)	0.5194	0.1018	(+)	0.9783	0.0060	(–)	0.9108	0.0404
	8	0.0177	0.0968	(+)	0	0	(+)	0.3265	0.1058	(+)	0.9729	0.1049	(–)	0.8772	0.1075
	10	0	0	(+)	0	0	(+)	0.6841	0.2941	(+)	0.9566	0.1610	(+)	0.9640	0.0594
DTLZ2	4	0.4956	0.0091	(+)	0.5702	0.0048	(–)	0.5738	0.0043	(–)	0.6012	0.0009	(–)	0.5119	0.0170
	6	0.4502	0.1828	(+)	0.7749	0.1213	(+)	0.9861	0.0005	(–)	0.9874	0.0028	(–)	0.9617	0.0142
	8	0.6287	0.0687	(+)	0.6445	0.0218	(+)	0.9999	0.0000	(=)	0.9998	0.0003	(=)	0.9986	0.0013
	10	0.8819	0.0267	(+)	0.9122	0.0039	(+)	1.0000	0.0000	(=)	1.0000	0.0000	(=)	1.0000	0.0000
DTLZ3	4	0.5173	0.0117	(–)	0.5944	0.0037	(–)	0.4323	0.0784	(+)	0.6048	0.0031	(–)	0.4870	0.0241
	6	0.8714	0.1256	(+)	0.7589	0.2487	(+)	0.9970	0.0021	(+)	0.9998	0.0008	(+)	0.9998	0.0004
	8	0.5564	0.1259	(+)	0.0344	0.0774	(+)	0.8970	0.2723	(+)	1.0000	0	(=)	1.0000	0
	10	0.4770	0.1052	(+)	0.2391	0.0707	(+)	1.0000	0.0000	(=)	1.0000	0	(=)	1.0000	0
DTLZ4	4	0.5217	0.0091	(=)	0.5497	0.0494	(–)	0.5940	0.0052	(–)	0.4995	0.1110	(+)	0.5009	0.1058
	6	0.7608	0.1209	(+)	0.9171	0.0519	(+)	0.9980	0.0001	(=)	0.9920	0.0062	(=)	0.9909	0.0088
	8	0.8969	0.0361	(+)	0.8763	0.0149	(+)	1.0000	0.0000	(–)	0.9999	0.0001	(=)	0.9999	0.0001
	10	0.9524	0.0135	(+)	0.9296	0.0065	(+)	1.0000	0.0000	(=)	1.0000	0.0000	(=)	1.0000	0.0000
DTLZ5	4	0.7797	0.0010	(–)	0.7641	0.0082	(–)	0.7676	0.0051	(–)	0.7721	0.0021	(–)	0.6402	0.1523
	6	0.8370	0.0068	(–)	0.6706	0.1093	(+)	0.8656	0.0040	(–)	0.8365	0.0068	(–)	0.7210	0.1273
	8	0.8209	0.0141	(–)	0.4208	0.1636	(+)	0.8751	0.0039	(–)	0.8512	0.0080	(–)	0.7320	0.0970
	10	0.8335	0.0166	(–)	0.4491	0.1325	(+)	0.8795	0.0031	(–)	0.8786	0.0061	(–)	0.7442	0.1092
DTLZ6	4	0.8993	0.0501	(–)	0.9139	0.0244	(–)	0.9281	0.0081	(–)	0.9349	0.0008	(–)	0.7890	0.2109
	6	0.5453	0.0484	(+)	0.2882	0.0467	(+)	0.9864	0.0030	(–)	0.9853	0.0030	(–)	0.8901	0.0585
	8	0.5262	0.0465	(+)	0.4263	0.0219	(+)	0.9885	0.0023	(–)	0.9877	0.0039	(–)	0.9298	0.0520
	10	0.5880	0.0467	(+)	0.4732	0.0243	(+)	0.9898	0.0012	(–)	0.9876	0.0031	(–)	0.9144	0.0515
DTLZ7	4	0.1581	0.0060	(+)	0.1844	0.0059	(–)	0.1924	0.0094	(–)	0.1885	0.0023	(–)	0.1660	0.0072
	6	0.0397	0.0121	(+)	0.1153	0.0113	(+)	0.1745	0.0109	(–)	0.1424	0.0083	(=)	0.1347	0.0123
	8	0.0563	0.0170	(+)	0.2345	0.1474	(+)	0.5154	0.0262	(+)	0.3428	0.1175	(+)	0.5536	0.0053
	10	0.1238	0.0280	(+)	0.3328	0.2144	(+)	0.3373	0.2226	(+)	0.6307	0.1579	(+)	0.8309	0.0141
+/=/-		**21/1/6**			**21/0/7**			**9/5/14**			**5/9/14**				

Results

Table 2: Mean and Standard Deviation of Hypervolume results for WFG problems

Problem	M	NSGA-II			SPEA2			KnEA			NSGAIII			Hierarchical	
WFG1	4	0.9716	0.0027	(=)	0.9822	0.0004	(–)	0.9695	0.0042	(=)	0.9567	0.0548	(+)	0.9650	0.0136
	6	0.9955	0.0005	(–)	0.9970	0.0003	(–)	0.9863	0.0025	(=)	0.9230	0.0756	(+)	0.9851	0.0045
	8	0.9986	0.0002	(–)	0.9989	0.0001	(–)	0.9878	0.0027	(=)	0.8813	0.0861	(+)	0.9917	0.0047
	10	0.9992	0.0001	(–)	0.9993	0.0000	(–)	0.9928	0.0026	(=)	0.8531	0.1084	(+)	0.9966	0.0013
WFG2	4	0.5578	0.0200	(=)	0.5847	0.0269	(=)	0.5460	0.0231	(+)	0.5541	0.0618	(+)	0.5611	0.0264
	6	0.5157	0.0300	(–)	0.5850	0.0257	(–)	0.4955	0.0240	(–)	0.5267	0.0633	(–)	0.2976	0.1568
	8	0.5045	0.0244	(–)	0.6333	0.0049	(–)	0.4709	0.0349	(=)	0.5951	0.0124	(–)	0.4826	0.0758
	10	0.5247	0.0203	(–)	0.6339	0.0040	(–)	0.5519	0.0387	(–)	0.5776	0.0140	(–)	0.4203	0.1115
WFG3	4	0.2581	0.0024	(=)	0.2598	0.0023	(=)	0.2597	0.0035	(=)	0.1909	0.0562	(+)	0.2521	0.0045
	6	0.1697	0.0073	(–)	0.1680	0.0072	(–)	0.1473	0.0119	(+)	0.0739	0.0258	(+)	0.1545	0.0056
	8	0.1468	0.0057	(–)	0.1457	0.0054	(–)	0.1064	0.0102	(–)	0.0468	0.0215	(+)	0.0749	0.0195
	10	0.1325	0.0045	(–)	0.1292	0.0062	(–)	0.0892	0.0114	(–)	0.0037	0.0039	(+)	0.0405	0.0244
WFG4	4	0.3102	0.0117	(+)	0.3472	0.0071	(–)	0.3778	0.0049	(–)	0.3372	0.0472	(=)	0.3399	0.0073
	6	0.2286	0.0122	(+)	0.2822	0.0127	(+)	0.3484	0.0144	(=)	0.2298	0.0829	(+)	0.3471	0.0120
	8	0.3391	0.0197	(+)	0.4114	0.0140	(+)	0.4223	0.0192	(+)	0.4479	0.0510	(+)	0.4867	0.0188
	10	0.3271	0.0142	(+)	0.4102	0.0147	(+)	0.4488	0.0239	(+)	0.3803	0.1385	(+)	0.5299	0.0208
WFG5	4	0.2328	0.0081	(+)	0.2686	0.0029	(–)	0.2619	0.0043	(–)	0.2647	0.0034	(–)	0.2555	0.0055
	6	0.1830	0.0125	(+)	0.2330	0.0077	(–)	0.1547	0.0191	(+)	0.2438	0.0094	(–)	0.2216	0.0171
	8	0.1879	0.0175	(–)	0.3011	0.0068	(–)	0.1896	0.0184	(–)	0.2666	0.0275	(–)	0.1379	0.0412
	10	0.1875	0.0140	(–)	0.2708	0.0110	(–)	0.1737	0.0224	(–)	0.2767	0.0201	(–)	0.1082	0.0268
WFG6	4	0.2129	0.0206	(+)	0.2663	0.0118	(+)	0.2200	0.0213	(+)	0.2710	0.0265	(=)	0.2748	0.0109
	6	0.1365	0.0365	(+)	0.1801	0.0307	(–)	0.0877	0.0290	(+)	0.2203	0.0251	(–)	0.1413	0.0404
	8	0.1243	0.0254	(+)	0.2018	0.0203	(–)	0.1083	0.0207	(+)	0.2181	0.0533	(–)	0.1415	0.0376
	10	0.1263	0.0284	(–)	0.1792	0.0160	(–)	0.0877	0.0201	(+)	0.1966	0.0345	(–)	0.1173	0.0329
WFG7	4	0.4375	0.0106	(–)	0.4794	0.0040	(–)	0.4884	0.0038	(–)	0.4296	0.0774	(=)	0.4246	0.0160
	6	0.4673	0.0087	(=)	0.5327	0.0047	(–)	0.5424	0.0057	(–)	0.4381	0.0844	(+)	0.4648	0.0156
	8	0.5138	0.0089	(–)	0.5765	0.0037	(–)	0.5789	0.0108	(–)	0.2919	0.1725	(+)	0.4789	0.0203
	10	0.5454	0.0099	(–)	0.6118	0.0037	(–)	0.5461	0.0372	(–)	0.3196	0.1031	(+)	0.5329	0.0223
WFG8	4	0.0997	0.0248	(+)	0.1338	0.0238	(+)	0.0285	0.0204	(+)	0.1943	0.0201	(=)	0.1961	0.0184
	6	0.0645	0.0239	(+)	0.0588	0.0157	(+)	0.0111	0.0072	(+)	0.1164	0.0175	(+)	0.1559	0.0121
	8	0.0500	0.0173	(+)	0.0980	0.0132	(+)	0.0480	0.0092	(+)	0.1689	0.0158	(=)	0.1654	0.0157
	10	0.0410	0.0141	(+)	0.0771	0.0185	(+)	0.0380	0.0070	(+)	0.1504	0.0202	(=)	0.1570	0.0129
WFG9	4	0.4061	0.0234	(+)	0.4783	0.0297	(–)	0.5094	0.0243	(–)	0.4766	0.0288	(–)	0.4433	0.0214
	6	0.3861	0.0194	(–)	0.5121	0.0409	(–)	0.5797	0.0327	(–)	0.5247	0.0366	(–)	0.3785	0.0514
	8	0.4528	0.0220	(=)	0.6056	0.0379	(–)	0.6233	0.0578	(–)	0.6679	0.1267	(–)	0.4570	0.0906
	10	0.5212	0.0199	(+)	0.6792	0.0322	(–)	0.6317	0.0917	(–)	0.6947	0.0738	(–)	0.6106	0.0854
+/=/-		15/5/16			8/2/26			13//7/16			16/6/14				

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Discussion

- We have conducted Wilcoxon's rank-sum test to obtain the statistical significance and presented the mean and standard deviation results of Hypervolume results in the tables 1 and tables 2.
- The algorithm with best results are presented in the bold and shaded with grey color.
- From the hypervolume results presented in the tables 1 and 2, we can observe that the proposed method outperforms the NSGA-II algorithm and performs competitively when compared with the SPEA2, KnEA, and NSGA-III

	NSGA-II	**SPEA2**	**KnEA**	**NSGA-III**	**Hierarchical**
+/=/-	36/6/22	29/2/33	30/12/22	21/15/28	

Multi/Many-objective Approaches for Next Release Problem

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Introduction

One common problem that the companies face is to decide what requirements should be implemented in the next release of the software. Some reasons that a company needs to find the ideal set of requirements:

1. Different levels of importance for software requirements
2. Some software requirements that are customer requests
3. The different requirement of times, costs, and efforts to be met

Next Release Problem?

The aim of the next release problem (NRP) is to find the most suitable set of tasks to include in the next release for a software product, to minimize the cost and to maximize the customer satisfaction based on optimization objectives

- ❑ Single objective
- ❑ Multi-objective

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Why Optimization in NRP?

- The aim of a development study is to analyze how to evaluate the minimum requirements for the fair selection of demands for five objectives of the multi/many-objective including the maximum profit of the customers.
- All current multi-objective NRP are aimed at two aims, namely profits cost, or profits and fairness.
- The pareto frontier is a general method of resolving the multi-objective NRP, which means the collection of optimal solutions currently offered. Users select requirements for balancing two overlapping objectives for their next release, based on such a muti-objective NRP.
- However, an organization must at the same time deal with three or more deadlines to assess the scope of the specifications.

Problem Statement

1. The number of clients is indicated by:

$$U = \{u_1, u_2, \dots, u_m\}$$

2. The set of all the requirements to be taken into account is shown by:

$$R = \{r_1, r_2, \dots, r_n\}$$

3. A certain amount of resources i.e. the cost of production, must be allocated for the i mplementation of every need. The following is a value vector:

$$C = \{c_1, c_2, \dots, c_n\}$$

Objective Formulation

1	The minimum of requirement costs	$minimize\ f_1(X) = \sum_{r_j \in R(X)} c_j$
2	The maximum of costumer profits	$minimize\ f_1(X) = \sum_{r_j \in R(X)} c_j$
3	The coverage of requirements for customers	$minimize\ f_3(X) = \sigma(\lvert R(s_i)\rvert)$
4	The fairness of customers	$minimize\ f_4(X) = \sigma\left(\frac{\lvert R(s_i)\rvert}{\lvert A(s_i)\rvert}\right)$
5	The fairness of resource allocation	$minimize\ f_5(X) = \sigma\left(\sum_{r_j \in R(s_i)} c_j\right)$

Evolutionary Approaches

[1] Y. Zhang, M. Harman, and S. A. Mansouri, "The multi-objective next release problem," in *Proceedings of the 9th annual conference on Genetic and evolutionary computation*, 2007, pp. 1129-1137.

[2] J. J. Durillo, Y. Zhang, E. Alba, and A. J. Nebro, "A study of the multi-objective next release problem," in *2009 1st International Symposium on Search Based Software Engineering*, 2009, pp. 49-58.

[3] J. J. Durillo, Y. Zhang, E. Alba, M. Harman, and A. J. Nebro, "A study of the bi-objective next release problem," *Empirical Software Engineering*, vol. 16, pp. 29-60, 2011.

[4] X. Cai, O. Wei, and Z. Huang, "Evolutionary approaches for multi-objective next release problem," *Computing and Informatics*, vol. 31, pp. 847--875, 2012.

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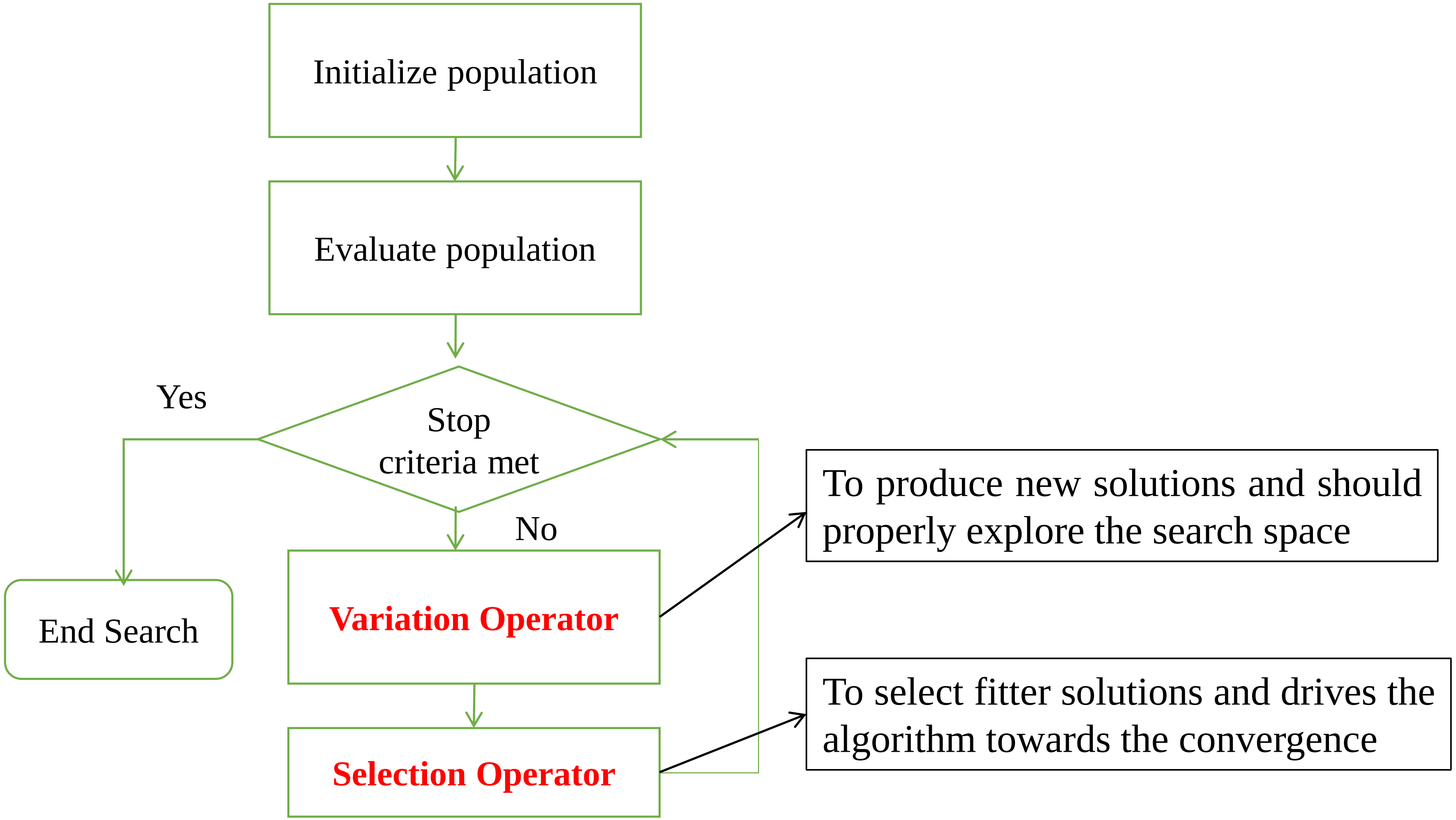
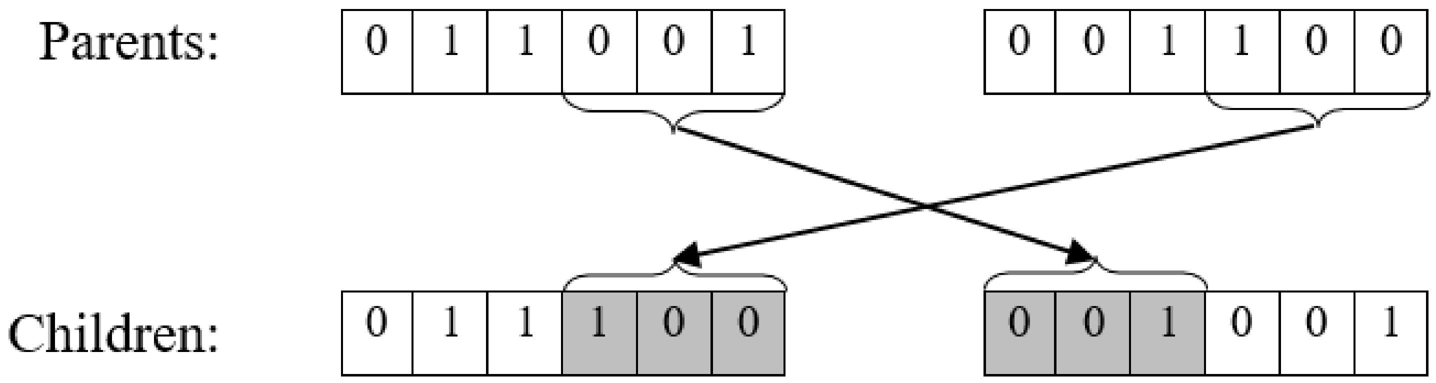
[6] J. Geng, S. Ying, X. Jia, T. Zhang, X. Liu, L. Guo, *et al.*, "Supporting Many-Objective Software Require ments Decision: An Exploratory Study on the Next Release Problem," *IEEE Access*, vol. 6, pp. 60547-60 558, 2018.

General Framework of Evolutionary Algorithm



Crossover

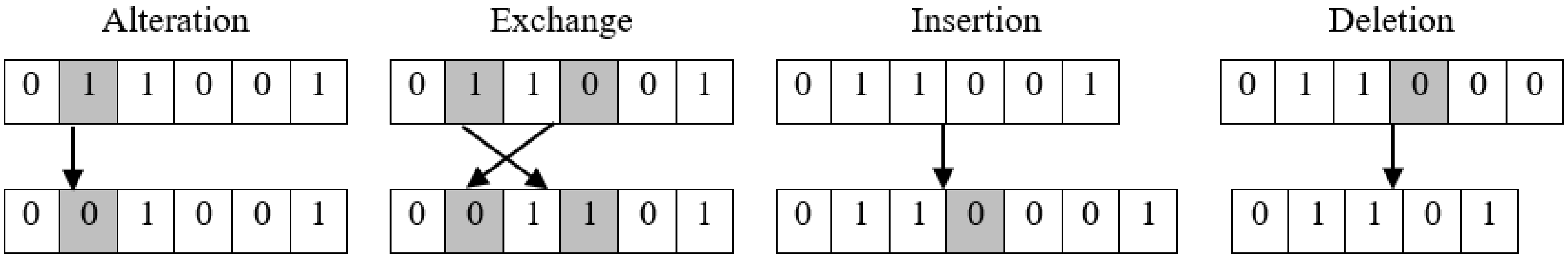
Crossover is a system in which more than one (usually two) parent solutions are taken from and children are created.
The image below is showing a template in which two parents are separated from the third bit and two children are engendered. Crossover methods can be more complex than they can, by splitting the parents into more than two parts and providing a cap of bits, but the principle remains the same.



Mutation

Each genetic algorithm has a mutation operator to increase its diversity with in the population. As Figure below shows, there are different mechanisms for a mutation: the alteration, the exchange, the insertion and removal. The likelihood of mutation needs to be selected well in order to progress slowly.

0.001, 0.01 or $\frac{1}{length}$ should be used in publications.



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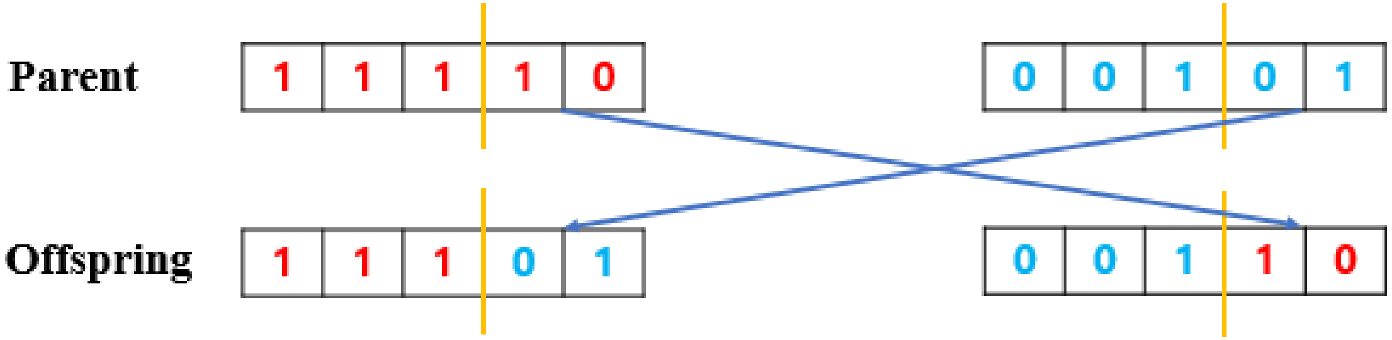
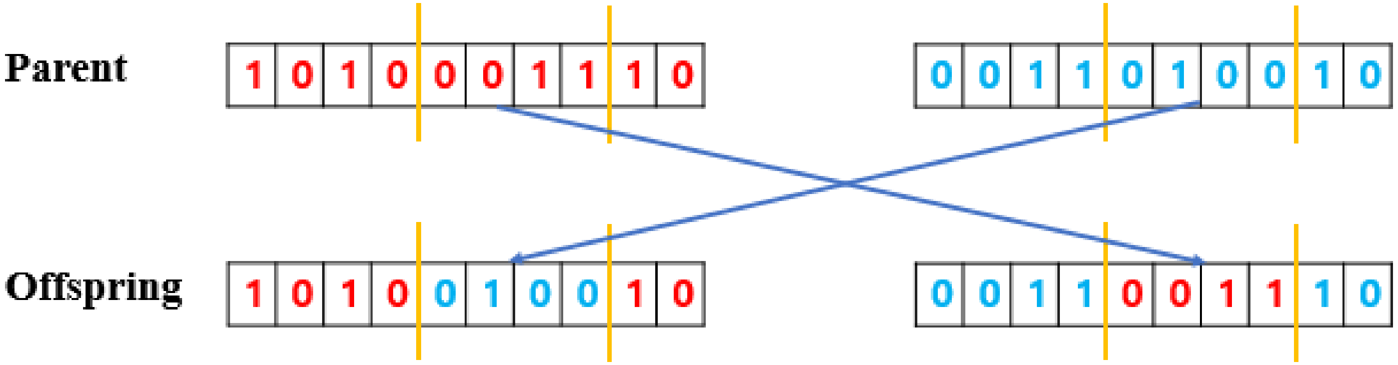
❑ Single Point Crossover

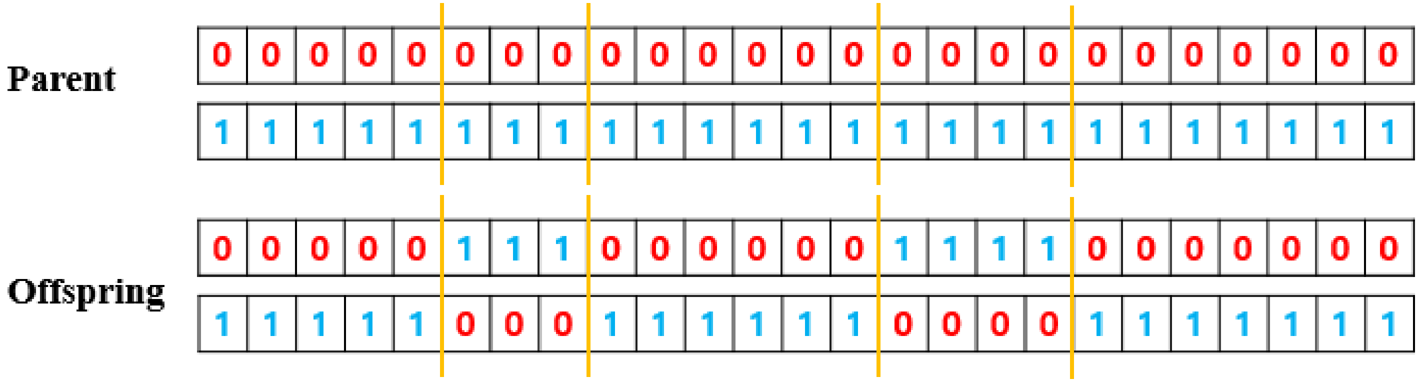


❑ Two Point Crossover



Existing crossover Operators

❑ Multi-parent Crossover



❑ Binomial Crossover

$$z'_{i,j} = \begin{cases} y'_{i,j}, & if\,(rand(0,1) \leq CR \mid j = j_r) \\ x'_{i,j}, & otherwise \end{cases}$$

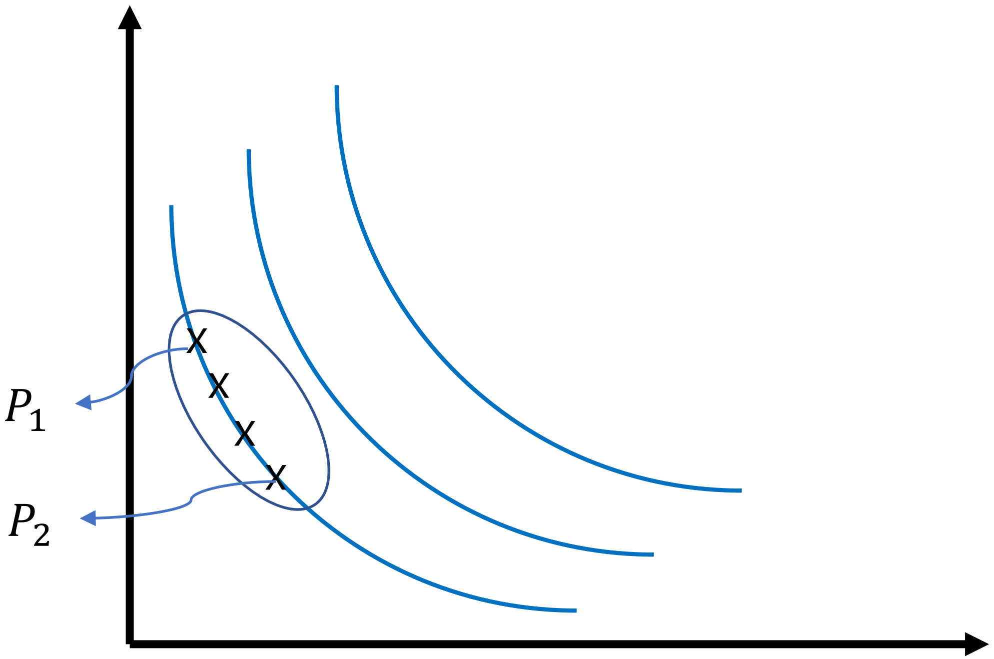
Existing Mutation Operation

- **Bit-wise Mutation**

  Bit-wise mutation is operator which attempted to mutate every bit (alter the bit to its complement) with a probability p_m independently to the outcome of mutation to other bits.

Proposed Mutation Operation

- **Radius Random Mutation**



0	1	0	1

1	0	0	1

1	0	1	0

1	1	0	0

0.75	0. 5	0.25	0.5

0.3	0. 5	0.28	0.9

Experimental Analysis

- This work have executed 30 runs with 250 generations for each run, every algorithm and every instance of problem.
- Because we deal with stochastic algorithms, a statistical analysis of the results obtained needs to be carried out in order to compare them with some confidence.

NRP Dataset

Instance	Problems							
	e1	e2	e3	e4	g1	g2	g3	g4
Requirements	3502	4254	2844	3186	2690	2650	2512	2246
Customers	536	491	456	399	445	315	423	294
Requirement cost	1-7	1-7	1-7	1-7	1-7	1-7	1-7	1-7
Customer profit	10-50	10-50	10-50	10-50	10-50	10-50	10-50	10-50
Requests by customer	4-20	5-30	4-15	5-20	4-20	5-30	4-15	5-20

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Hypervolume Results

Problems	NSGAII-SPCBMW		NSGAII-SPCradiusmut		NSGAII-TPCradiusmut		NSGAII-BNCradiusmut		NSGAII-MrPCradiusmut	
No.of objectives = 2										
NRP-e1	0.2103	0.0141	0.2998	0.0422	0.3001	0.0511	0.2801	0.0499	0.3111	0.0371
NRP-e2	0.1674	0.0104	0.2713	0.0403	0.2873	0.0420	0.2561	0.0584	0.2992	0.0479
NRP-e3	0.2169	0.0141	0.2886	0.0435	0.2908	0.0484	0.2722	0.0416	0.3054	0.0374
NRP-e4	0.2034	0.0133	0.2831	0.0500	0.2636	0.0409	0.2774	0.0431	0.3135	0.0453
NRP-g1	0.2263	0.0157	0.2884	0.0388	0.2981	0.0402	0.2639	0.0448	0.3036	0.0412
NRP-g2	0.2392	0.0155	0.2954	0.0348	0.3074	0.0436	0.2891	0.0434	0.3097	0.0352
NRP-g3	0.2299	0.0150	0.2887	0.0484	0.2762	0.0470	0.2639	0.0443	0.2923	0.0333
NRP-g4	0.2461	0.0116	0.2740	0.0410	0.2838	0.0577	0.2758	0.0536	0.2966	0.0376

Hypervolume Results

Problems	ISDE+-SPCBMW		ISDE+-SPCradiusmut		ISDE+-TPCradiusmut		ISDE+-BNCradiusmut		ISDE+-MrPCradiusmut	
No.of objectives = 2										
NRP-e1	0.2016	0.0110	0.5126	0.0166	0.5136	0.0165	0.4690	0.0171	0.5163	0.0177
NRP-e2	0.1708	0.0103	0.5138	0.0147	0.5064	0.0151	0.4704	0.0234	0.5086	0.0154
NRP-e3	0.2070	0.0131	0.5122	0.0168	0.5091	0.0197	0.4615	0.0167	0.5088	0.0150
NRP-e4	0.2133	0.0131	0.5166	0.0169	0.5150	0.0158	0.4766	0.0131	0.5089	0.0167
NRP-g1	0.2052	0.0157	0.5096	0.0163	0.5090	0.0162	0.4713	0.0203	0.5067	0.0194
NRP-g2	0.2245	0.0163	0.5171	0.0133	0.5136	0.0137	0.4751	0.0235	0.5108	0.0187
NRP-g3	0.2133	0.0130	0.5128	0.0146	0.5103	0.0165	0.4694	0.0211	0.5108	0.0173
NRP-g4	0.2149	0.0175	0.5101	0.0147	0.5076	0.0165	0.4659	0.0187	0.5016	0.0170

Hypervolume Results

	NSGAII-SPCBMW		NSGAII-SPCradiusmut		NSGAII-TPCradiusmut		NSGAII-BNCradiusmut		NSGAII-MrPCradiusmut	
No. of Objectives = 5										
NRP-e1	0.0618	0.0082	0.0758	0.0134	0.0704	0.0137	0.0660	0.0110	0.0750	0.0121
NRP-e2	0.0710	0.0078	0.0832	0.0071	0.0820	0.0060	0.0694	0.0140	0.0854	0.0059
NRP-e3	0.0598	0.0049	0.0680	0.0114	0.0782	0.0079	0.0672	0.0049	0.0700	0.0154
NRP-e4	0.0652	0.0093	0.0748	0.0092	0.0764	0.0062	0.0786	0.0205	0.0726	0.0094
NRP-g1	0.0620	0.0141	0.0734	0.0101	0.0690	0.0053	0.0594	0.0124	0.0696	0.0079
NRP-g2	0.0778	0.0105	0.0816	0.0092	0.0836	0.0061	0.0752	0.0142	0.0866	0.0083
NRP-g3	0.0624	0.0091	0.0784	0.0075	0.0622	0.0062	0.0684	0.0061	0.0718	0.0068
NRP-g4	0.0712	0.0033	0.0756	0.0135	0.0828	0.0197	0.0704	0.0130	0.0764	0.0099

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Conclusion

In this study researchers and practitioners in the area of code and search techniques can provide valuable feedback. Certain problem formulations that take account of different sets of goals and specifications, and the development of techniques that enable software engineers to take decisions, are also important to study.

In addition, this could lead to the need to find more efficient solutions. It is also interesting to examine the scope of such strategies, when demand and/or consumer numbers increase. A method that allows the systemic development of instances with desired functions will be required to reach this goal; we intend to develop a problem generator for MONRP instances in this regard.

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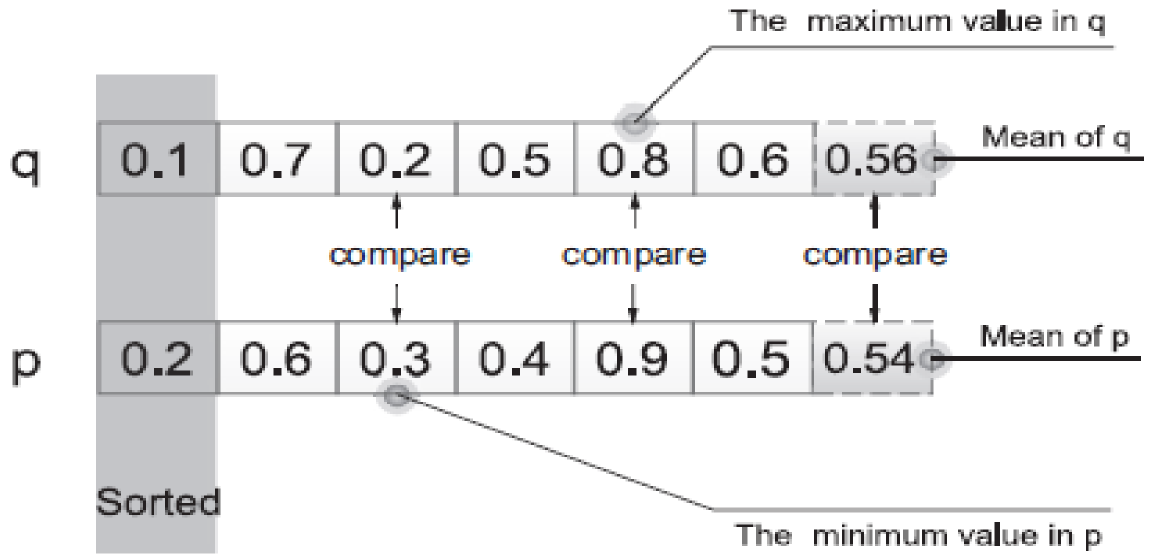
Thank You

Approximate non-dominated sorting (A-ENS)



Shift Density Estimation

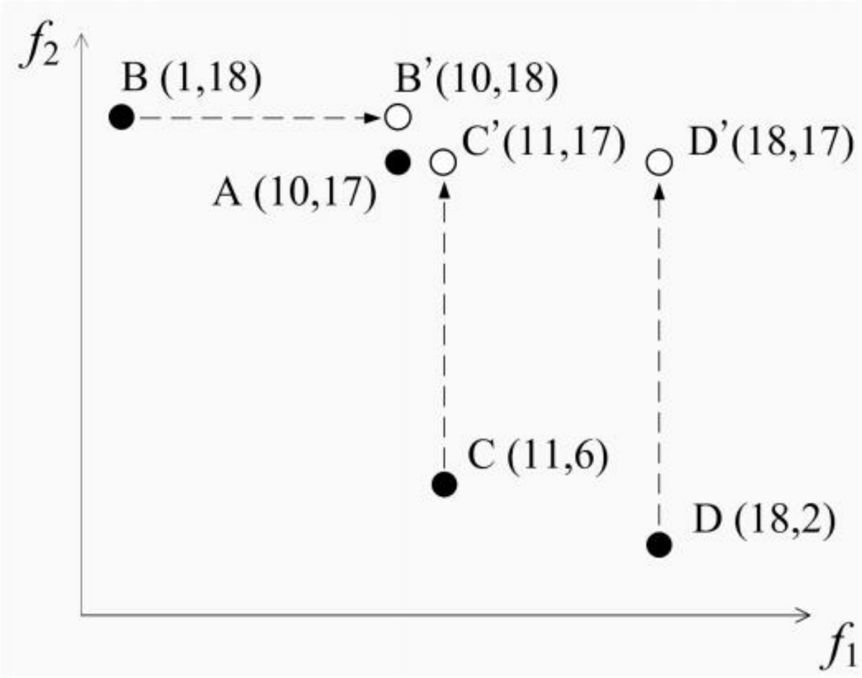


Fig. 2. An illustration of shift-based density estimation in a bi-objective minimization scenario. To estimate the density of individual **A**, individuals **B**, **C**, and **D** are shifted to **B**$'$, **C**$'$, and **D**$'$, respectively.