Contribution Title*

First Author[1[0000−1111−2222−3333]], Second Author[2,3[1111−2222−3333−4444]], and
Third Author[3[2222−−3333−4444−5555]]

[1] Princeton University, Princeton NJ 08544, USA
[2] Springer Heidelberg, Tiergartenstr. 17, 69121 Heidelberg, Germany
lncs@springer.com
http://www.springer.com/gp/computer-science/lncs
[3] ABC Institute, Rupert-Karls-University Heidelberg, Heidelberg, Germany
{abc,lncs}@uni-heidelberg.de

Abstract. bet-and-run and moea/d

1 Introduction

Multiobjective Optimization Problem have m multiple objective functions that must be optimized simultaneously.

Maximize[1] $F(x) = (f_1(x), f_2(x), ..., f_m(x))$,

subject to x in Ω.

- $F(x)$ objective functions; - f_i is the i-th objective to be maximized; - x is the decision vector; - Ω is the decision space.

[1] All definitions are for maximization. Following inequalities should be reversed if the goal is to minimize.

Many real-world scientific and engineering are MOP. Water quality control, Groundwater pollution re-mediation, Design of marine vehicles [3]. Petrol extraction. Hard problems: to balance the interests of the multi-objective as a whole is hard.

Objectives may be conflicting - The goal is to find good trade-off.

- Set of solutions.

Set of *optimum solutions* - Pareto set.

- Non-dominated solutions: no single solution provides a better trade-off in all objectives.

1Let $u = (u_1, ..., u_m)$ and $v = (v_1, ..., v_m)$ vectors in Ω (the decision space). - $\forall i : u$ dominates v if $f_i(u) \leq f_i(v)$ and $\exists j : f_j(u) < f_j(v)$. - u dominates v, v is dominated by u, u is better that v.

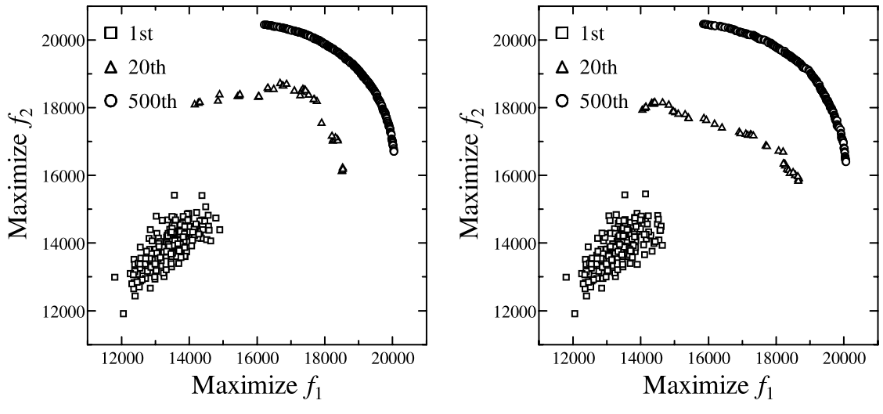
A point x^* in Ω is called *Pareto Optimal* if no other point dominates x^*.

The set of all Pareto Optimal is called the Pareto Set.

$P^* = \{x \in \Omega : \nexists$ y $\in \Omega$ and $F(y) \leq F(x)\}$

Pareto Front is the image of the Pareto Set in the objective space. PF = $F(x) = (f_i(x), ..., f_m(x)) : x \in P^*$

* Supported by organization x.



(a) The weighted sum. (b) The weighted Tchebycheff.

Fig. 1. Pareto Set - [6]

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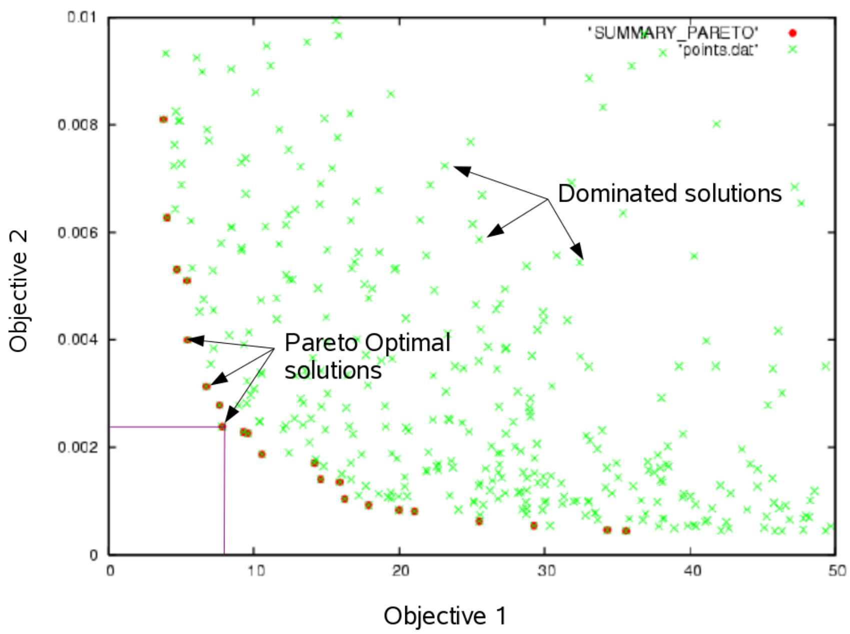

2 MOEA/D

MOEA/D represents a class of population-based meta-heuristics for solving Multi Objective Problems (MOPs).

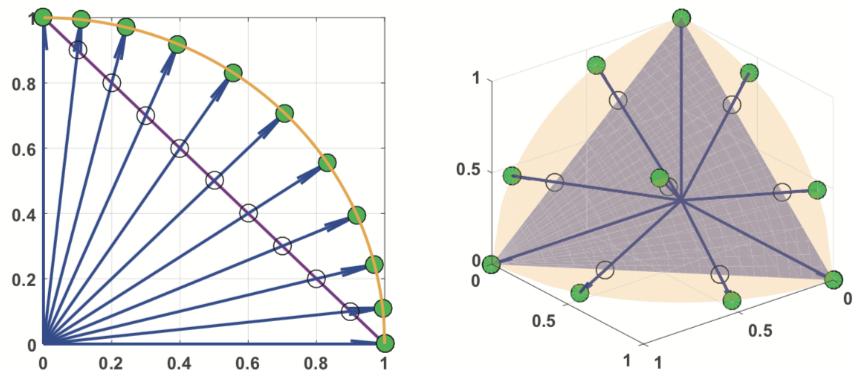

Fig. 2. Decomposition - 2 and 3 objectives, [2]

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It is based on decomposition - one kind of scalarizing function One multi-objective problem becomes various single-objective sub-problems. All sub-problems are solved in parallel. A decomposition strategy generates weight vectors that defines the sub-problems.

Why use decomposition?

It may be good at generating an even distribution of solutions in MOPs It reduces the computation complexity when compared to other algorithms (NSGA-II) [8]. An optimal solution of a set of scalar optimization problems can be a Pareto optimal solution, under mild conditions All solutions can be compared based on their objective function values It is simple to find a solution to multi single-objective problems than for a multi-objective problem Fitness assignment and diversity maintenance become easier to handle.

$f_3(x) = F * w_3$

In general, $f_i(x) = F * w_i$

Components of the MOEA/D

- Decomposition strategy: decomposes w/ weight vectors; - Aggregation function: weight vector =¿ single-objective sub-problems; - Neighbourhood assignment strategy: Relationship between sub-problems; - Variation Stack: New candidates solutions; - Update Strategy: Maintain/discard candidate solutions; - Constraint handling method: Constraint violation; - Termination Criteria: when to stop the search.

Variations Already Integrated

On-line Resource Allocation - proposed in the context of MOEA/D by [9]. Bet-and-Run: A kind of restart strategy - in the context of single-objective problems (SOP) by [4].

What is Online Resource Allocation

- On-line Resource Allocation (ONRA) is an adaptation strategy that aim to adjust the behaviour of an algorithm in an on-line manner to suit the problem in question.

How it affects MOEA/D [9].

- Some sub-problems can be more difficult to approximate that others. To better explore them, different computational resources are allocated to different sub-problems.

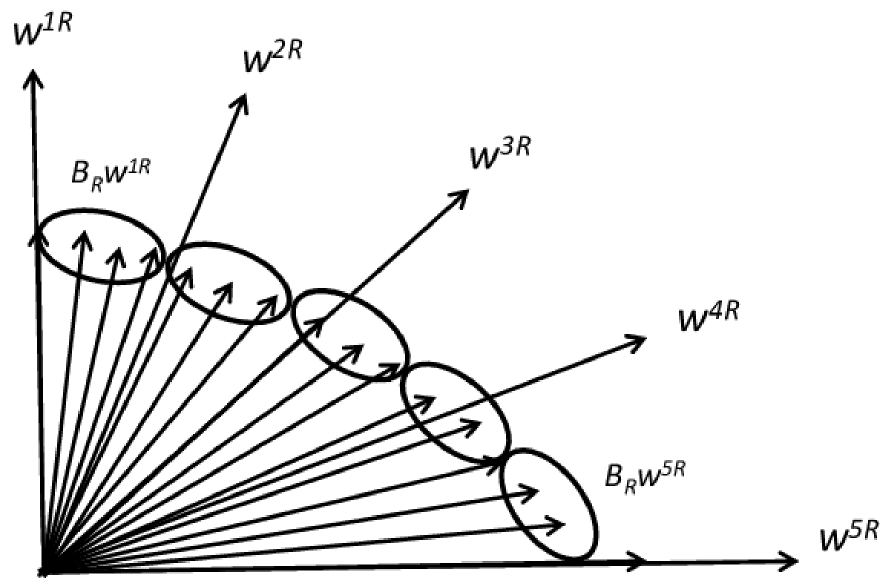

Fig. 3. Decomposition and Aggregation Function - [2].

- The resources re-allocated is *the number of functions evaluations*. - From an equal amount to every sub-problem to an amount related to the difficulty of the sub-problem.

Restart Strategy

- Restart Strategy is a strategy used to avoid heavy-tailed running time distributions [5].

- If a execution of an algorithm does not conclude within a pre-determined limit or if the solution quality is unsatisfactory, we restart the algorithm @lissovoi2017theoretical.

Bet-and-Run framework

- It is defined in @fischetti2014exploiting. as a number of short runs with randomized initial conditions, bet on the most promising run, and bring it to completion.

- To the best of our knowledge, only applied with EA in the context of SOP.

How it affects MOEA/D - [7].

- Initialisation can have a small beneficial effect even on very easy functions.

- Countermeasure when problems with promising and deceptive regions are encountered.

- Additional speed-up heuristic.

3 Evaluation Metrics

Evaluation Metrics

Unary Indicators

- Measure Pareto Sets independently. - Power is restricted. - Cannot tell in general if a set is better than another. - Focus on problem dependent and specifics. - Assumptions and knowledge should be specified. 1. Hyper-volume. 2. Error ratio. 3. Distance from reference set.

Binary Indicators

- Theoretically have no limitations. - Analysis and presentation of results more difficult.

1. R1, R2, R3 indicators. 2. ε-Indicator. 3. Binary Hyper-volume.

Hypervolume Considerations

- Is complete - If, and only if $HV(A) > HV(B) \implies A$ is not worse than B. - Is weakly compatible - $HV(A) > HV(B) \implies \not B$ dominates A. - Assumptions - All points of a Pareto Set under consideration dominate the reference point. - @ishibuchi2018specify proposed a method to specify the reference point from a viewpoint of fair performance comparison.

Considerations - A large population size is **always** more beneficial than a small one. - Measures both the convergence toward the Pareto Front and the diversity of non-dominated solutions. - A monotonic increase of the hyper-volume over time cannot always be ensured. - For MOEA/D that is always true.

ε-Indicator Considerations - It compares 2 Pareto Sets. - It indicates which set is better and how much better - If A is better than B $\implies I_\varepsilon(B, A) > 0$. - If $I_\varepsilon(A, B) \leq 0$ and $I_\varepsilon(B, A) > 0 \implies A$ is better than B.

The benchmark used are the DTLZ and the ZDT group of functions.

DTLZ are easy [1].

4 Experiment Design

4. maxiter 300. 5. Based on the common variation: MOEA/D (variations 1 and 2 from MOEADr) and MOEA/D-DE.

Overview of the experiments

DTLZ[1-7] MOP benchmark- Available from the MOEADr package. both 3 and 2 objectives. ZDT[1-6] MOP benchmark- Available from the MOEADr package, only for 2 objectives.

Number of evaluations: 50000 or 100000 for 4 objectives Compared with their HV - normalized between 0 and 1 (based on the fair comparison paper). 30 repetitions. box-plots Kruskal-Wallis (data non-normal data, used in the literature)

Configurations and Parameters

Control - Based on the common variation: MOEA/D (variation1) and MOEA/D-DE as in preset_moead Control and ONRA - parameters: dt = 20 Ben-and-run Ben-and-run and ONRA - parameters: dt = 20

Dt - interval that control the resources allocation. From the proposal paper, there is no much sensibility. Decomposition method used - SLD, with H being 199 for 2D and 19 for 3D number of dimensions - 60 All other parameters are defined by preset_moead

Bet-and-run

Phase 1 of the bet-and-run strategy is using the epsilon indicator. 40 instances. It needs two Pareto sets. The first is the Pareto set of a bet instance while the other is the Pareto set from the control algorithm executed with 1% of the number of interactions. Phase 2 uses the 60% rest of max interactions.

5 Results

Analysis are done with

6 Conclusion

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