

# A New Dynamically Reference Point Adaptation Mechanism in indicator-based EMOA based on weak convergence detection

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**Abstract**—The abstract goes here.  
**Keywords**—keyword 1; keyword 2

## I. INTRODUCTION

This demo file is intended to serve as a “starter file” for IEEE conference papers produced under L<sup>A</sup>T<sub>E</sub>X using IEEEtran.cls version 1.8a and later. I wish you the best of success.

mds

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### A. Subsection Heading Here

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## II. REFERENCE POINT ADAPTATION

When hypervolume(HV) is used in indicator-based algorithms, one important thing to be considered is that how to specified the reference point. Before calculating the HV values, reference point needs to be chosen in advance. However, it is not suggested that the reference point is set only once at the beginning. [?] This may cause a very far away reference point from solutions for those problems with a very large feasible space. As the solutions set is gradually converging to the pareto front, during the iteration of the algorithm procecess (As shown in Fig. 1). There is a big problem when applying this strategy to some problems with specific pareto front shape, for example, the inverted-DTLZ1 problem with a inverted-triangular pareto front in 3 dimensions, that many solutions of the final solutions set will distribute at the boundary of the pareto front (Fig. 2) [?], [?]. Although it has no effect on the distributions of solutions set in problems with triangular pareto front in 3 dimensions (Fig. 3), it is necessary using reference point adaptation during the algorithm progress.

In many algorithms including SMS-EMOA [?], the reference point is adapted based on the following rules:

$$\text{estimatedreferencepoint} = \text{reestimatednadirpoint}, r = 1.1. \quad (1)$$

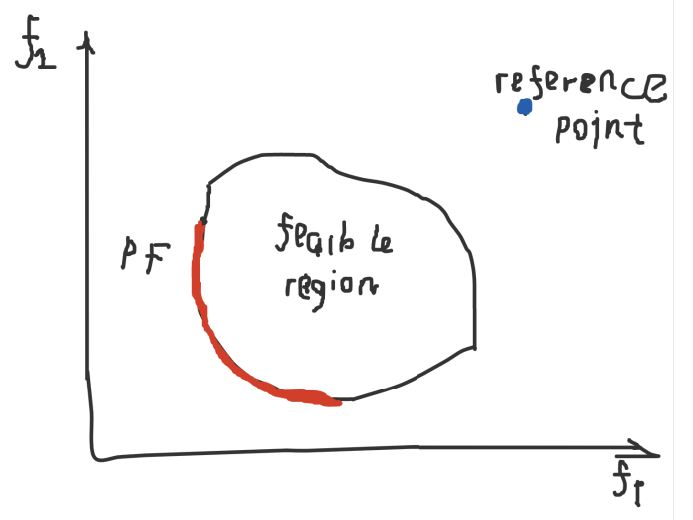


Fig. 1. The reference point for a large feasible space. PF can be far away from reference point.

Note that the estimated nadir point is the nadir point in current population. When the solutions in the current population is obtained, we use hypervolume as indicator to evaluate the performance of the solutions set. Then the reference point used to calculate the hypervolume is calculated by the formula above.

## III. DYNAMIC MECHANISM

Basically the Evolutionary Multi-objective Optimization Algorithm can be separate into two stages:

1) *Early Stage*: In this stage, all the solutions are far away from pareto front. The main task is to converge the solutions to pareto front. This stage is also called Convergence Stage.

2) *Final Stage*: In this stage, all the solutions are in or near the pareto front. So the main task is to make the distribution of solutions more evenly in the pareto front. This stage is also called Diversity Stage.

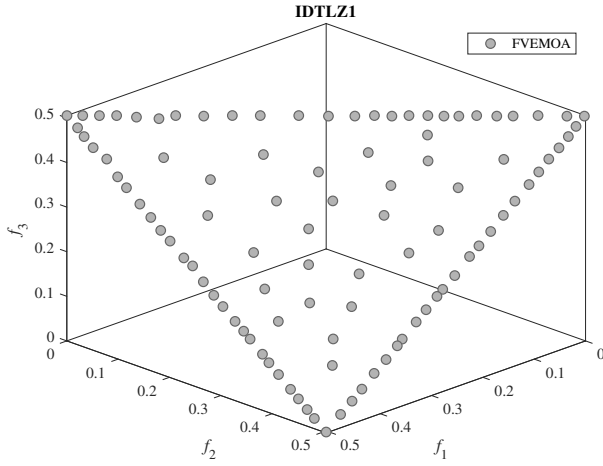


Fig. 2. The final distribution of solutions set in inverted-DTLZ1 problem. The algorithm is FVEMOA with a reference point adaptation strategy when  $r=2$ .

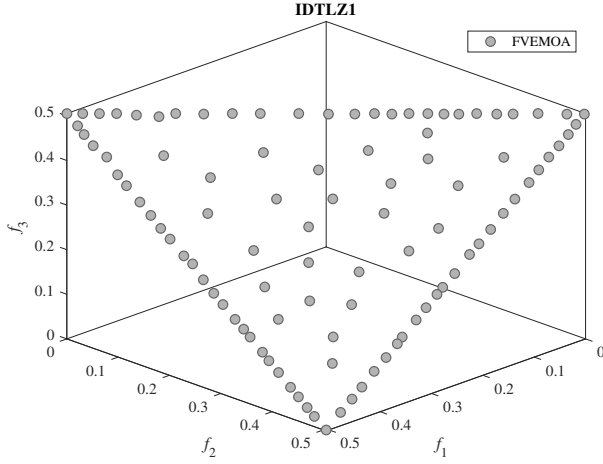


Fig. 3. The final distribution of solutions set in DTLZ1 problem. The algorithm is FVEMOA with a reference point adaptation strategy when  $r=2$ .

For different purposes in these two stages, the  $r$  should be treated differently [?]. Not only the reference point but also the value of  $r$  needs to be adapted in each iteration of algorithm. This is called dynamically reference point adaptation.

Unfortunately, the research on how to specified  $r$  is limited. Only a few papers [?], [?], [?], [?] did some research on reference point. The reason is that, the effect of the location of the reference point on the pareto front is not fatal on some benchmark problems, especially triangular pareto front. But in fact, on some specific problems, the distribution of solutions on pareto front strongly depends on the location of the reference point. The sensitivity about value of  $r$  for solutions is also observed on some real world problems, for example, distance minimization problems. This observation Potential shows the usefulness of the dynamically reference point adaptation [?].

A. *reference point specification for optimal distribution*

some text

B. *reference point specification for fast convergence*

some text

C. *linearly decrease mechanism*

some text

#### IV. NEW DYNAMIC MECHANISM

In this section, we will introduce a new mechanism that combines a weak convergence detection criterion. As we have explained before, a slightly larger  $r$  is suggested at the initial stage of the algorithms. But for well diversity at the final stage, it is needed to set  $r$  to its optimal value  $(1 + 1/H)$ . So

A. *weak convergence detection*

some text LSCD: least squares convergence detection

#### V. COMPUTATIONAL EXPERIMENTS

A. *settings*

#### VI. CONCLUSION

The conclusion goes here.

#### ACKNOWLEDGMENT

The authors would like to thank... [2]

#### REFERENCES

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- [2] H. pka and P. W. Daly, *A Guito L<sup>A</sup>T<sub>E</sub>X*, 3rd ed. Harlow, England: Addison-Wesley, 1999.