

Weak Convergence Detection based Dynamic Reference Point Specification in SMS-EMOA

Weiduo Liao, Ke Shang, Hisao Ishibuchi

Department of Computer Science and Engineering

Southern University of Science and Technology, Shenzhen, China

Email: 11849249@mail.sustech.edu.cn; kshang@foxmail.com; hisao@sustech.edu.cn

Abstract—In the field of indicator-based evolutionary multi-objective optimization algorithms(indicator-based EMOAs), Hypervolume(HV) is a popular indicator, which is the only pareto-compliant indicator up to now. But recently, a paper shows that the position of reference point will influence the diversity of the final solutions of HV-based EMOAs when applying to the inverted-triangular Pareto front problems, by influencing the HV contribution of the external solutions. In this paper, we state this phenomenon and introduce the reference point specification with the dynamic mechanism in terms of necessity. Then we propose a new dynamic mechanism based on weak convergence detection. In our approach, the simple Least Squares and the information of nadir point are used to detect the convergence. After that, we examine the difference between this new dynamic mechanism with a state-of-the-art linearly decrease mechanism.

Keywords—reference point adaptation; indicator-based algorithm; hypervolume; evolutionary multi-objective optimization; behavior; dynamic mechanism; convergence detection

I. INTRODUCTION

In the field of evolutionary multi-objective optimization algorithms (EMOAs), many researchers focus on various indicators including Hypervolume(HV) [1], R2 [2], ϵ_+ indicator [3] and IGD [4]. The indicators are designed for different purposes, and have their own strong points and drawbacks. Different from IGD, HV does not need the pre-knowledge of the shape of the Pareto front(PF) and is the only pareto-compliant indicator up to now [5]. But with a heavy computation load of HV computation [6], the HV-based algorithms get poor performances in running time when dealing with problems which have more than three objectives, which is so-called Many-Objective Optimization Problems(MaOPs).

SMS-EMOA [7] is a basic HV-based algorithm. The HV contribution is used to determine which solution to be discarded in the algorithm. After proposing the SMS EMOA, in order to reduce the heavy computation cost of HV computation, many new indicators or new methods have been proposed to estimate the HV. For example, HypE use a Monte Carlo simulation technology to estimate the effect of HV [8]; R2 indicator bases on a standard weighted Tchebycheff function

[2] and a new R2 is proposed by Shang et al [9]. Recently, an improved SMS-EMOA with adaptive resource allocation has been proposed to reduce the number of HV calculations [10]; In 2015, a simple and fast version of SMS-EMOA [7], so-called FV-EMOA, has been proposed [11]. In order to further reduce the bottleneck of high time complexity for calculating the HV contributions, the FV-EMOA considers the fact that the HV contribution of a single solution is only associated with partial solutions rather than the whole solution set [11]. Based on this point, the FV-MOEA reduces the computational cost greatly.

The specification of the reference point is one of the important but easy to be ignored parts in HV computation, for that the effect on many problems including DTLZ [12] are not so significant. But it has been reported that the position of reference point strongly influences the value of HV contribution of the external solutions on the problems with inverted-shape PFs [13]–[15]. A suitable set of reference point position for flat PFs has been sufficiently investigated in Hisao et al. [14]. And a dynamic reference point specification mechanism has also been proposed in [16]. Another strategy proposed is to use two reference points in HV-based EMOA [17]. In this paper, the dynamic mechanism is stated in two different stages of the algorithm running process. At the early stage, for a better searching behavior of the algorithm, the reference point should be set a little worse than the suggested position at the beginning. Then with a dynamic mechanism, the reference point is gradually decreasing to the suggested position following the iteration.

After that, we propose a new dynamic reference point specification mechanism with a weak convergence detection in HV-based EMOA. The simple least squares and the logarithm value of nadir point as a convergence indicator are used in this weak convergence detection. Given w_l generations as a window, if the slope of linear regression is below one threshold, we report the convergence. The comparison of two dynamic mechanisms and simple reference point specification(without dynamic mechanism) is represented in the experiment section. On some specific problems, for example the multi-objective distance minimization problems [18], our weak convergence detection mechanism outperforms the linearly decrease mechanism.

The remainder of this paper is organized as follows. Firstly, we briefly introduce the basic idea of reference point speci-

This work was supported by the Program for Guangdong Introducing Innovative and Entrepreneurial Teams (Grant No. 2017ZT07X386), Shenzhen Peacock Plan (Grant No. KQTD2016112514355531), the Science and Technology Innovation Committee Foundation of Shenzhen (Grant No. ZDSYS201703031748284), the Program for University Key Laboratory of Guangdong Province (Grant No. 2017KSYS008), and National Natural Science Foundation of China (Grant No. 61876075).

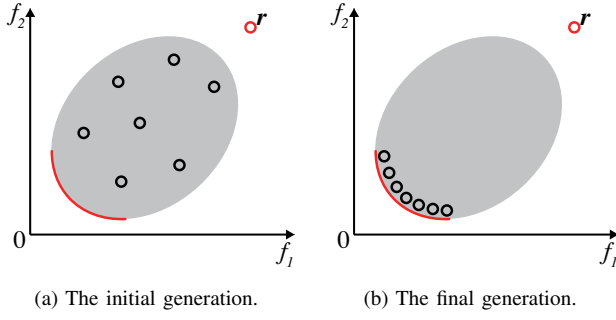


Fig. 1: The reference point is set with a large feasible space. The PF can be far away from reference point. The gray region shows the feasible region and the red arc is the corresponding PF. The red circle r is the reference point calculated by the initial solutions in (1a) which is randomly generated. After some generations, the current solutions reach to the five black circles in (1b), which is far away from the reference point.

cation by a simple example in Section II. Then, we explore the details of the reference point specification mechanism in two stages of the algorithm, which elicits the necessity of using dynamic mechanism in Section III. After that, we state the details of the dynamic reference point specification mechanism and introduce a proposed linearly decrease mechanism in Section IV. Then the details of the new dynamic mechanism with a weak convergence detection proposed in this paper is in Section V. And we report our computational experiments of SMS-EMOA with several triangular and inverted-triangular problems in Section VI. Our experiments are performed on 10-dimension problems for clearly comparing of two dynamic mechanisms and simple reference point adaptation (without dynamic mechanism). Finally, the conclusion is shown in Section VII.

II. REFERENCE POINT SPECIFICATION IN HV-BASED EMOA

When HV is used in indicator-based algorithms, one important thing to be considered is how to specify the reference point. Before calculating the HV values, a reference point needs to be specified 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 shown in Fig. 1), as the solution set is gradually converging to the PF with the process of the algorithm.

There is a big problem when applying this strategy to some problems with special PF shape. For example, the inverted-DTLZ1 [19] has an inverted-triangular PF, so many solutions in the final solution set will distribute on the boundary of the PF (Fig. 2a) [14]–[16]. Although it has no effect on the distributions of solution set in problems with triangular PF (Fig. 2c comparing with Fig. 2d), it is necessary using a good reference point specification method during the algorithm progress. The reason is explained in detail in [15].

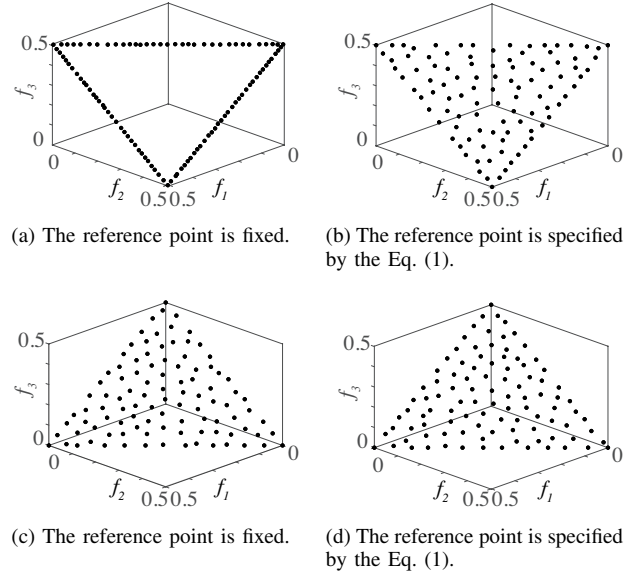


Fig. 2: The final distribution of solution set in the inverted-DTLZ1(2a and 2b) and the DTLZ1 problem(2c and 2d). The algorithm is SMS-EMOA with population size = 100, evaluation number = 20000. 2a and 2c: the reference point is calculated only once at the initial step; 2b and 2d: the reference point is specified by the Eq. (1) with $r = 1.1$. All the solutions in the final distribution are on the boundary of the PF in (2a), which shows the bad effect of a faraway reference point on the final distribution of inverted-triangular problems. This bad effect can not be observed on triangular problems in (2c).

In the original SMS-EMOA [7], the reference point is specified as the estimated nadir point increased by 1.0 (in two-dimension, a sufficiently large reference point is chosen). But in current implementation, the following mechanism is always used:

$$\mathbf{R} = r * \mathbf{N}, \mathbf{R}, \mathbf{N} \in \mathbb{R}^m. \quad (1)$$

Note that \mathbf{R} is the reference point in each generation, and \mathbf{N} is the estimated nadir point of the last front of the current population. r is specified as 1.1 in PlatEMO [20], a well-known EMO framework. The specification of reference point is one of the important parts in the HV-based algorithm implementation. In the source code of PlatEMO, the values of r in HV-based algorithms are chosen as follow: 1.1(SMS-EMOA [7]) and 1.2(HypE [8]). When the solutions in the current population are obtained, we use HV as the indicator to evaluate the performance of the solution set. Then the reference point used to calculate the HV is calculated by the formula above.

But actually, fixing the r value to 1.1 is not suggested, especially on problems with the inverted-triangular PF [13]. The research on specifying the value of r is limited, for the reason that, the effect of the location of the reference point on the PF is not fatal on some benchmark problems, for example, the problems with triangular PF.

In [13]–[15], the suggested value of r is investigated

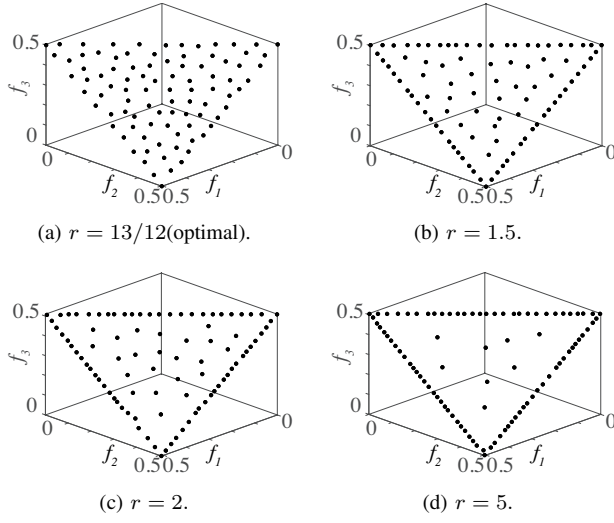


Fig. 3: The final distribution of solution set on the inverted-DTLZ1 problem. The algorithm is SMS-EMOA with population size = 91($H = 12$) and evaluation number = 20000. $r = 13/12$ is the optimal setting and we observed an evenly distribution in (3a). As the increasing of r , solutions are more likely to be on the boundary (3b-3d).

on linear PF problems. Specifically, on inverted-triangular problems(inverted-DTLZ1 [15] etc.), in order to have same HV contribution, the interval between two boundary solutions should be the same as that between two inner solutions. In [13], the suggested value of r is:

$$r = 1 + \frac{1}{H}. \quad (2)$$

H is the number of solutions intervals in 2-dimension and the number of intervals on each boundary of PF in many-dimension. The idea is from MOEA/D [21], in which the H is used for generating uniformly distributed weight vectors [16]. Given the population size μ and dimensionality m , the value of H can be calculated by the following formula:

$$C_{m-1}^{H+m-1} \leq \mu < C_{m-1}^{H+m}. \quad (3)$$

In Fig. 3a, $r = 13/12$ ($H = 12$) is the optimal setting for a 91-individual 3-dimensional inverted-DTLZ1 problem and an optimal distribution is observed. In Fig. 3b - Fig. 3d, the inner solutions are decreased and move to the boundary of PF as the increasing of r .

III. EXPLORATION ON REFERENCE POINT SPECIFICATION MECHANISM IN DETAIL

Basically, the process of Evolutionary Multi-objective Optimization Algorithm can be separated into two stages:

1) *Early Stage*: In this stage, all the solutions are far away from the PF. The main task is to converge the solutions to the PF. We also call this stage the convergence stage.

2) *Final Stage*: In this stage, all the solutions are in or near the PF. So the main task is to make the distribution of

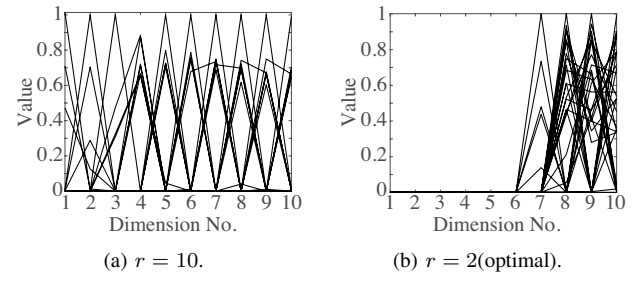


Fig. 4: The final distribution of SMS-EMOA on 10-objective DTLZ2 problems with different settings of r . The population number is 30($H = 1$), total evaluation number is 10000.

solutions more evenly in the PF. We also call this stage the diversity stage.

A. Specify the Value of r for Better Searching Behavior

In the early stage, solution set is not close to the PF, which makes the estimated ideal and nadir points far away from true ideal and nadir points, for the reason that they are calculated by current solutions in each generation. And considering the problems with 10 objectives, if the external solutions have the same HV contribution with the inner solutions, the exploration of solutions will be poor. As a result, some dimensionalities of solutions will be missing and the breadth-diversity [22] will be poor. An example is given in Fig. 4. The first 6 dimensionalities are all 0 for the solutions obtained by SMS-EMOA on 10-objective DTLZ2 problems(Fig. 4b). In [16], a larger value of r than $1 + 1/H$ is suggested in the early stage.

B. Specify the Value of r for Optimal Distribution

When algorithm reaches to the final stage, all solutions are near the PF, r should be specified as $1 + 1/H$, as in Eq. (2), in order to get an optimal solutions distribution. That is, $r(T) = 1 + 1/H$. On inverted-triangular problems, the distribution of solutions on PF strongly depends on the value of r (as shown in Fig. 3).

The sensitivity of the value of r on the solutions distribution is also observed on some real-world problems, for example, distance minimization problems. This observation potential shows the usefulness of the dynamical reference point specification [16].

IV. DYNAMIC REFERENCE POINT SPECIFICATION MECHANISM

For different purposes in the two stages, the r should be treated differently [16]. Not only the reference point but also the value of r needs to be adapted in each iteration of the algorithm. This is called dynamical reference point specification. Based on the Eq. (1), we define the dynamic reference point specification as:

$$\mathbf{R} = r(t) * \mathbf{N}, \mathbf{R}, \mathbf{N} \in \mathbb{R}^m, t = 0, 1, \dots, T, \quad (4)$$

where T is the total number of generations, and $r = r(t)$ is a function of the current generation t . The value of r is adapted during the process of the algorithm.

A. Linearly Decrease Mechanism

Based on the theory above, r is suggested to be specified dynamically at different stages of the algorithm (at early stage, a larger r is chosen; at final stage, $r = 1 + 1/H$ is chosen). But unfortunately, there is no best mechanism on how to specify the value of r dynamically **outperforming** the others in all problems and all experiment settings. One mechanism may be the best when working on some specific experiment conditions, but may not be good on other conditions.

In [16], a linearly decrease mechanism has been proposed:

$$r(t) = r_{Initial} \frac{(T-t)}{T} + (1 + 1/H) \frac{t}{T}, t = 0, 1, \dots, T, \quad (5)$$

where T is the total number of generations, and $r_{Initial}$ is the initial value of r , which is larger than $1 + 1/H$. It is a simple and practical mechanism. In (5), the value of r starts from $r_{Initial}$, then gradually decreases to the suggested value in a linearly **decrease** process.

In the next section, we will propose another good dynamic mechanism based on weak convergence detection criterion **outperforms** simple linearly decrease mechanism on some specific problems.

V. A NEW DYNAMIC REFERENCE POINT SPECIFICATION MECHANISM

In this section, we will introduce a new mechanism that uses a weak convergence detection criterion to decide whether to change the value of r from $r_{Initial}$ to $1 + 1/H$.

As we have explained before, a larger r is suggested at the early stage of the algorithms. But for good diversity at the final stage, it is needed to set r to its optimal value ($1 + 1/H$). For this purpose, **we detect whether the algorithm is converged or not**. If solutions are all close to the PF, we change the value of r to $r_{Optimal}$; otherwise, we set value of r to $r_{Initial}$. The mechanism is shown below:

$$r(t) = \begin{cases} r_{Initial}, & t < t_{Convergent} \\ 1 + 1/H, & t \geq t_{Convergent} \end{cases} \quad t = 0, 1, \dots, T. \quad (6)$$

$r(t)$ equals to $r_{Initial}$ before reaching **to** the convergent generation $t_{Convergent}$, and changes to $1 + 1/H$ after $t_{Convergent}$. $t_{Convergent}$ is determined by a weak convergence detection criterion.

A. Weak Convergence Detection

Consider many convergence detection papers [23]–[29], various indicators including convergence detection indicators are **using** to detect the stagnation. They focus on the accuracy of convergence, which is not the purpose in our approach for the reason that after algorithm convergent, we still need some generations in order to get even distribution of solution set. We summarize our weak convergence detection criterions as follow:

1) *inaccuracy*: It is not necessary to have an accurate convergence detection. The convergence can be reported if current solutions are close to the PF. In other words, the

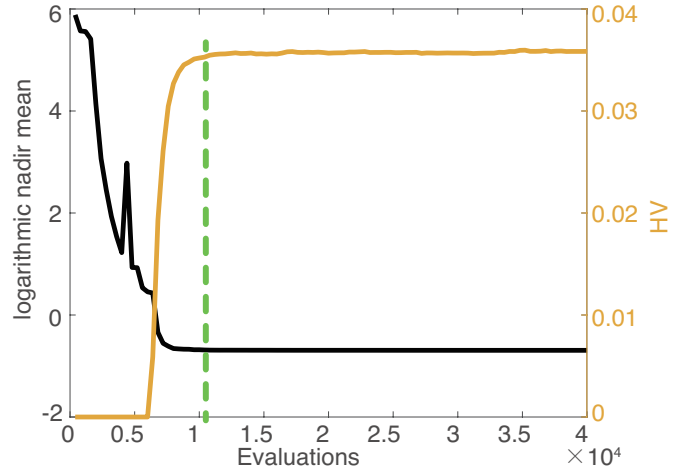


Fig. 5: Example of nadir point and HV value on 3-objective inverted-DTLZ1 problem with SMS-EMOA algorithm. The yellow curve is the change of HV while the black curve is the change of the logarithmic nadir point. The green dotted line shows the convergence detection.

estimated ideal and nadir points based on the current solutions are close to the true ideal and nadir points.

2) *saving time*: We should not spend too much time in convergence detection for the reason that the state-of-the-art indicator-based algorithms such as SMS-EMOA and HypE, are time-consuming when the dimension is very high.

We are discussing the effect of reference points in calculating HV. It seems to be a good idea to use **progress indicator HV** as our convergence detection indicator, for that, we have **calculated HV in each generation in the HV-based EMOA**. But during the process of algorithm, the reference point is calculated by Eq. (1) in each generation. As a result, we can not just simply compare HV calculated in algorithm among different generations.

We are trying on some other good indicators satisfying our convergence detection criterions. Fig. 5 shows the change of HV and nadir point on SMS-EMOA with 3-objective inverted-DTLZ1 problem. When current solutions are close to the PF, the estimated nadir point of current solutions is close to the true nadir points. This implies that the estimated nadir point can be a good indicator for our purpose. But for some problems with a large feasible region, the moving distance of the estimated nadir point in the early generations is larger than that near convergence. So we consider the logarithm. And considering the possible bad variance of the indicator, finally, we use the best logarithmic nadir point so-far as our indicator. More specifically, for a minimization problem, we consider

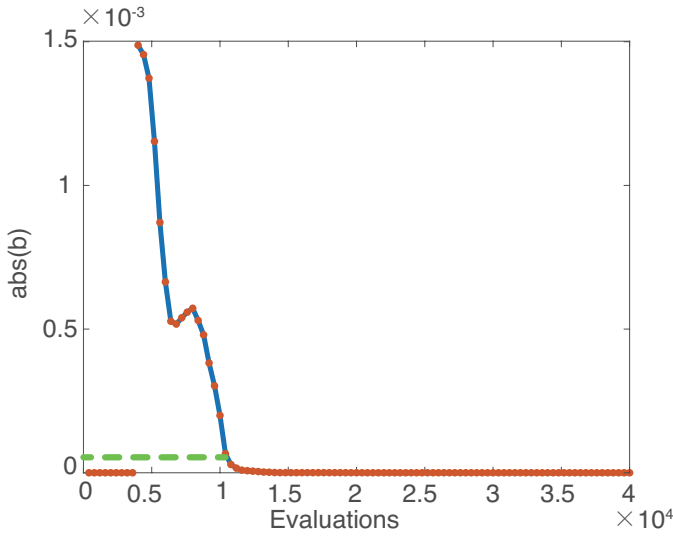


Fig. 6: Example of $|b|$ on inverted-DTLZ1 3-dimension problem (window size = 4000 evaluations with population size = 100). The green dotted line shows the threshold.

the indicator I as follows:

$$\begin{aligned} \mathbf{N}_t &= [f_{t1}, f_{t2}, \dots, f_{tm}]^T \in \mathbb{R}^m, \\ I_0 &= \frac{1}{m} \sum_{i=1}^m \ln f_{0i}, \\ I_t &= \min(I_{t-1}, \frac{1}{m} \sum_{i=1}^m \ln f_{ti}), t = 1, 2, \dots, T, \end{aligned} \quad (7)$$

where T is the total number of generations, \mathbf{N}_t is the estimated nadir point at the t^{th} generation with m objectives: $f_{t1}, f_{t2}, \dots, f_{tm}$. I_0 is the initial indicator calculated by the initial population. And I_t is the minimum value before the t^{th} generation (including the t^{th} generation).

After choosing the indicator, the next step is to detect the stagnation of the indicator. We use a basic linear regression method called Simple Least Squares [30] with a simple least squares convergence detection strategy introduced in [24]. If the absolute value of the slope of the indicator is below a threshold, the convergence is reported. Briefly speaking, for a simple linear regression $I = a + bt$, the intercept a and slope b of the t^{th} generation can be calculated with the following matrix-based formula:

$$\begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \sum t_i^2 & \sum t_i \\ \sum t_i & w_l \end{bmatrix}^{-1} * \begin{bmatrix} \sum t_i * I_{t_i} \\ \sum I_{t_i} \end{bmatrix} \quad (8)$$

where w_l is the length of the chosen window and t_i is the evaluated number in the chosen window. The value of slope b is shown in Fig. 6 (Note that the value in the first w_l evaluations is 0, and we should not consider the first w_l evaluations).

With the above Eq. (8), the convergence detection criterion is defined as:

$$convergence = |b| < thres \quad (9)$$

The **chosen** of the $thres$ value is not so important as the report ahead or delay is not fatal to the algorithm or to the final solution set. We choose $thres$ value as 10^{-5} after some experimental computation with the window size $w_l = 4000$. If we do not change the window size, this threshold can be applied to other problems or indicator-based algorithms because of a weak convergence detection purpose.

VI. COMPUTATIONAL EXPERIMENTS

A. Experimental Settings

To clearly represent the superiority of dynamically reference point specification and to ease the comparison process of two different dynamic mechanisms (linearly decrease mechanism and weak convergence detection mechanism), the mechanisms are ~~going to be~~ tested with the state-of-the-art algorithm SMS-EMOA [7]. The **problems** include: DTLZ [12], WFG [31], their minus-versions [32] and a multi-objective distance minimization problem(MPDMP) [18]. We test all the problems with 10 objectives. All the code in this section is implemented in PlatEMO framework [20] with the following settings:

- Population size: 30 ($H = 1$),
- Total evaluation number: 100,000 solution evaluations,
- Initial value of r ($r_{Initial}$): 10.
- Crossover: **simulated binary** (probability: 1.0),
- Mutation: **polynormal** (probability: $1/D$),
- Number of decision variables D :
 - 14 (DTLZ1 and minus-DTLZ1),
 - 2 (MPDMP),
 - 19 (other problems),
- Distribution index in Crossover and Mutation: 20,
- Number of runs: 20 runs.

B. Computational Results

The detailed algorithms are as **following**: SMS-EMOA-10 (SMS-EMOA [7] with $r = 10$), SMS-EMOA-Opt (SMS-EMOA with $r = 1 + 1/H$), SMS-EMOA-LD (SMS-EMOA with a linearly decrease mechanism), and SMS-EMOA-CD (SMS-EMOA with a weak convergence detection mechanism, proposed in this paper). We obtain the HV results after 100,000 evaluations for each algorithm. The computational results of the HV metric is shown in TABLE I and TABLE II. The best result in each row is highlighted in bold, and the worst result is shaded. The basic Wilcoxon signed-rank sum test is used in order to show the statistical significance for the algorithm comparing with SMS-EMOA-CD proposed in this paper. The three symbols “+”, “-”, “ \approx ” mean significantly better, significantly worse and no significant difference.

In the basic test problems(DTLZ1-4, WFG1-9), SMS-EMOA-Opt performs the worst (9 out of 13 significantly worse than SMS-EMOA-CD) among the algorithms in TABLE I. This phenomenon clearly show the bad searching behavior when applying $r = 1 + 1/H$ all the time, which is discussed in Section III. As for SMS-EMOA-10, we can not tell the differences with SMS-EMOA-CD, that the Wilcoxon signed-rank sum tests show almost all the results except one are “ \approx ”. This is because **that** the influence of reference point

TABLE I: HV mean and standard deviation over 20 independent runs for DTLZ and WFG problems.

Problem	M	D	SMS-EMOA-10	SMS-EMOA-Opt	SMS-EMOA-LD	SMS-EMOA-CD
DTLZ1	10	14	6.8448e-1 (4.61e-1) \approx	2.0261e-1 (2.23e-1) $-$	8.8369e-1 (2.00e-1) \approx	6.9062e-1 (3.95e-1)
DTLZ2	10	19	1.0234e+3 (4.72e-1) \approx	9.9315e+2 (3.94e+1) $-$	1.0234e+3 (7.28e-1) \approx	1.0184e+3 (1.85e+1)
DTLZ3	10	19	0.0000e+0 (0.00e+0) \approx	1.9068e+1 (8.53e+1) \approx	0.0000e+0 (0.00e+0) \approx	0.0000e+0 (0.00e+0)
DTLZ4	10	19	8.0029e+2 (2.21e+2) \approx	5.2691e+2 (1.79e+2) $-$	6.6262e+2 (2.17e+2) \approx	7.2840e+2 (2.26e+2)
WFG1	10	19	2.2025e+12 (2.55e+11) \approx	2.2597e+12 (2.64e+11) \approx	2.2005e+12 (1.81e+11) \approx	2.2601e+12 (3.42e+11)
WFG2	10	19	3.3604e+12 (2.92e+10) \approx	3.3493e+12 (2.39e+10) $+$	3.3487e+12 (7.64e+10) \approx	3.3420e+12 (8.46e+10)
WFG3	10	19	4.7217e-3 (1.04e-2) $-$	2.5310e-2 (3.07e-2) \approx	1.7230e-2 (2.35e-2) \approx	2.3443e-2 (2.84e-2)
WFG4	10	19	3.7667e+12 (1.77e+10) \approx	3.5602e+12 (9.48e+10) $-$	3.7585e+12 (3.74e+10) \approx	3.7737e+12 (1.63e+10)
WFG5	10	19	3.6535e+12 (7.68e+9) \approx	3.5027e+12 (1.16e+11) $-$	3.6555e+12 (8.64e+9) \approx	3.6523e+12 (1.93e+10)
WFG6	10	19	3.6082e+12 (7.78e+10) \approx	3.5432e+12 (6.24e+10) $-$	3.5829e+12 (5.75e+10) \approx	3.6099e+12 (4.49e+10)
WFG7	10	19	3.7967e+12 (7.58e+9) \approx	3.7326e+12 (5.73e+10) $-$	3.7959e+12 (1.35e+10) \approx	3.7922e+12 (1.27e+10)
WFG8	10	19	3.7512e+12 (1.51e+10) \approx	3.7087e+12 (3.64e+10) $-$	3.7613e+12 (1.13e+10) $+$	3.7524e+12 (1.23e+10)
WFG9	10	19	3.5727e+12 (1.85e+11) \approx	3.3072e+12 (2.80e+11) $-$	3.6302e+12 (1.57e+11) $+$	3.5146e+12 (2.31e+11)
$+/-/\approx$			0/1/12	1/9/3	2/0/11	

TABLE II: HV mean and standard deviation over 20 independent runs for minus-DTLZ, minus-WFG and MPDP.

Problem	M	D	SMS-EMOA-10	SMS-EMOA-Opt	SMS-EMOA-LD	SMS-EMOA-CD
minus-DTLZ1	10	14	4.3889e+28 (5.56e+26) \approx	4.4237e+28 (5.99e+26) \approx	4.4120e+28 (4.79e+26) \approx	4.3872e+28 (7.72e+26)
minus-DTLZ2	10	19	1.2299e+7 (1.38e+5) $-$	1.4737e+7 (1.55e+5) $-$	1.4891e+7 (1.11e+5) \approx	1.4844e+7 (1.45e+5)
minus-DTLZ3	10	19	1.1227e+35 (3.16e+33) $-$	1.3385e+35 (3.41e+33) \approx	1.3702e+35 (3.42e+33) \approx	1.3582e+35 (3.78e+33)
minus-DTLZ4	10	19	1.1638e+7 (2.11e+5) $-$	1.4899e+7 (1.20e+5) $+$	1.4895e+7 (1.27e+5) $+$	1.3585e+7 (1.57e+6)
minus-WFG1	10	19	4.4808e+10 (5.25e+8) \approx	4.4894e+10 (4.81e+8) \approx	4.4890e+10 (4.35e+8) \approx	4.4705e+10 (5.60e+8)
minus-WFG2	10	19	6.6225e+10 (1.05e+8) $-$	6.7628e+10 (7.51e+8) \approx	6.7870e+10 (3.31e+7) $-$	6.7907e+10 (1.60e+7)
minus-WFG3	10	19	6.3620e+10 (5.49e+8) \approx	6.4321e+10 (2.29e+8) $+$	6.3642e+10 (4.93e+8) \approx	6.3799e+10 (5.87e+8)
minus-WFG4	10	19	1.6478e+11 (3.22e+9) $-$	1.9896e+11 (2.20e+9) \approx	1.9752e+11 (2.39e+9) \approx	1.9260e+11 (1.34e+10)
minus-WFG5	10	19	1.6534e+11 (2.09e+9) $-$	1.9817e+11 (1.82e+9) \approx	1.9897e+11 (1.93e+9) \approx	1.9819e+11 (1.40e+9)
minus-WFG6	10	19	1.6532e+11 (2.11e+9) $-$	1.9865e+11 (1.83e+9) \approx	1.9989e+11 (2.03e+9) \approx	1.9960e+11 (1.94e+9)
minus-WFG7	10	19	1.6534e+11 (2.88e+9) $-$	1.9870e+11 (1.30e+9) $-$	1.9978e+11 (2.21e+9) \approx	1.9937e+11 (2.97e+9)
minus-WFG8	10	19	1.6808e+11 (1.46e+9) $-$	1.9932e+11 (1.56e+9) $-$	2.0220e+11 (1.71e+9) $+$	2.0065e+11 (1.77e+9)
minus-WFG9	10	19	1.6415e+11 (3.16e+9) $-$	1.9777e+11 (2.21e+9) \approx	1.9557e+11 (2.17e+9) $-$	1.9852e+11 (1.86e+9)
MPDP	10	2	1.4848e+5 (2.50e+2) $-$	1.5051e+5 (3.10e+2) $-$	1.5017e+5 (1.98e+2) $-$	1.5097e+5 (1.64e+2)
$+/-/\approx$			0/1/3	2/4/8	2/3/9	

on the triangular PF problems is small as discussed in [15]. 2 better results from SMS-EMOA-LD obtained indicate that SMS-EMOA-LD is slightly better than SMS-EMOA-CD on triangular PF problems.

In the results of inverted-triangular PF problems (minus-DTLZ1-4, minus-WFG1-9 and MPDP), SMS-EMOA-10 performs the worst(12 out of 14) in all experiments in average, and the Wilcoxon signed-rank sum tests show that almost all the results from SMS-EMOA-10 are significantly worse than SMS-EMOA-CD (11 out of 14 worse and no better results). The reason is that the r is 10 all the process of SMS-EMOA-10 algorithm and many solutions are on the boundary of PF. Comparing with SMS-EMOA-CD, SMS-EMOA-Opt(2 better but 4 worse) and SMS-EMOA-LD(2 better but 3 worse) are slightly worse on inverted-triangular PF problems. The result of MPDP shows that SMS-EMOA-CD is better among the four algorithms on some specific problems.

So we plot the runtime HV graph of 4 mechanisms (as shown in Fig. 7) on the 10-dimensional MPDP problem. In Fig. 7, the HV of SMS-EMOA-LD (the red curve) is gradually increased and finally reaches to the same level as SMS-EMOA-Opt, as the value of r is gradually decrease to $1 + 1/H$. The HV of SMS-EMOA-CD (the yellow curve) firstly reaches to a stable level similar to SMS-EMOA-10, for

that their values of r are both 10 before 4,500 evaluations. Then after reporting the convergence detection at about 4,500 evaluations, the value of r in SMS-EMOA-CD reaches to the optimal value $1 + 1/H$ and the HV increases. The reason are that the boundary solutions decrease, and on the other hand, the inner solutions increase. Finally, the HV of SMS-EMOA-CD is better than SMS-EMOA-Opt and SMS-EMOA-LD.

VII. CONCLUSIONS

In this paper, we emphasize the importance of reference point specification in indicator-based EMOA by a simple example. Without a good reference point specification mechanism, the diversity of the final solutions will be poor on inverted-shape PF problems. This phenomenon will not be observed on the triangular PF problems when reference point is worse than nadir point. Then we state the dynamic reference point specification mechanism with the illustration by two aspects:

1) *Better Searching Behavior*: In the early stage, the solutions may not be close to the true PF. A larger value of r can achieve a better searching behavior. We give an example of the DTLZ2 problem.

2) *Optimal Distribution*: Considering the flat triangular problems, the optimal setting of reference point is $r = 1 + 1/H$.

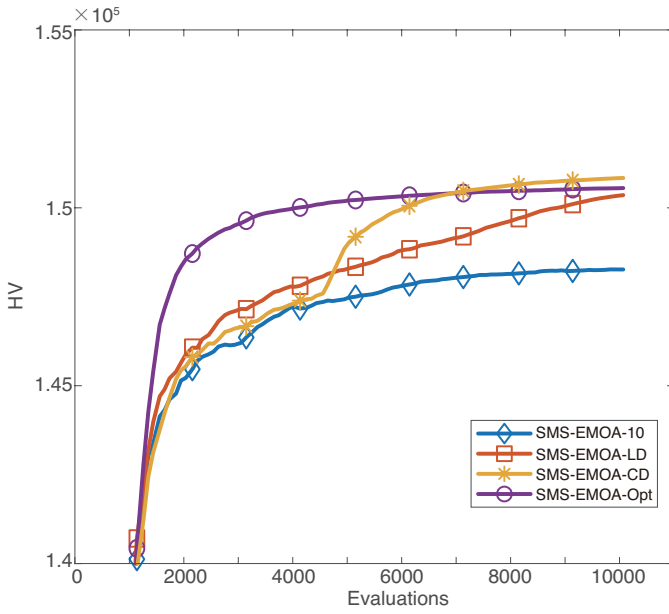


Fig. 7: The comparison of four mechanisms. The value of each point is the average of 20 independent runs in each evaluation and the problem is MPDMP.

We summarize the whole process of dynamic reference point specification mechanism as that, the value of r should be specified larger than $1 + 1/H$ at first and be equal to $1 + 1/H$ in the end, as in Eq. (4)-(6).

After that, a new dynamic reference point adaptation mechanism is proposed in this paper. A weak convergence detection mechanism is used. We apply our new dynamic mechanism on many test problems containing triangular, inverted-triangular PFs problems. The results show that SMS-EMOA with $r = 1 + 1/H$ performs the worst on the problems with triangular PF, and SMS-EMOA with $r = 10$ performs the worst on the problems with inverted-triangular PFs, which hint the superiority of dynamic mechanism. SMS-EMOA with weak convergence detection mechanism performs better or worse than SMS-EMOA with linearly decrease mechanism.

We compare our new mechanism with the proposed linearly decrease mechanism and find that on some problems, specifically the multi-objective distance minimization problems, our weak convergence detection mechanism outperforms the linear decrease mechanism.

In the future, we plan to further investigate the behavior of our new mechanism. A larger dimensionality of MaOPs should be considered and the problems with different PF shapes should be tested and analyzed detailedly. Our weak convergence detection mechanism can also be further improved.

REFERENCES

- [1] E. Zitzler and L. Thiele, "Multiobjective optimization using evolutionary algorithms: a comparative case study," in *International conference on parallel problem solving from nature*. Springer, 1998, pp. 292–301.
- [2] M. P. Hansen and A. Jaszkiewicz, *Evaluating the quality of approximations to the non-dominated set*. IMM, Department of Mathematical Modelling, Technical University of Denmark, 1994.
- [3] E. Zitzler, L. Thiele, M. Laumanns, C. M. Fonseca, and V. G. da Fonseca, "Performance assessment of multiobjective optimizers: An analysis and review," *Trans. Evol. Comp.*, vol. 7, no. 2, pp. 117–132, Apr. 2003. [Online]. Available: <http://dx.doi.org/10.1109/TEVC.2003.810758>
- [4] C. A. C. Coello and M. R. Sierra, "A study of the parallelization of a coevolutionary multi-objective evolutionary algorithm," in *Mexican International Conference on Artificial Intelligence*. Springer, 2004, pp. 688–697.
- [5] E. Zitzler, D. Brockhoff, and L. Thiele, "The hypervolume indicator revisited: On the design of pareto-compliant indicators via weighted integration," in *International Conference on Evolutionary Multi-Criterion Optimization*. Springer, 2007, pp. 862–876.
- [6] N. Beume, C. M. Fonseca, M. Lopez-Ibanez, L. Paquete, and J. Vahrenhold, "On the complexity of computing the hypervolume indicator," *IEEE Transactions on Evolutionary Computation*, vol. 13, no. 5, pp. 1075–1082, 2009.
- [7] N. Beume, B. Naujoks, and M. Emmerich, "Sms-emoa: Multiobjective selection based on dominated hypervolume," *European Journal of Operational Research*, vol. 181, no. 3, pp. 1653–1669, 2007.
- [8] J. Bader and E. Zitzler, "Hype: An algorithm for fast hypervolume-based many-objective optimization," *Evolutionary computation*, vol. 19, no. 1, pp. 45–76, 2011.
- [9] K. Shang, H. Ishibuchi, M.-L. Zhang, and Y. Liu, "A new $r2$ indicator for better hypervolume approximation," in *Proceedings of the Genetic and Evolutionary Computation Conference*, ser. GECCO '18. New York, NY, USA: ACM, 2018, pp. 745–752. [Online]. Available: <http://doi.acm.org/10.1145/3205455.3205543>
- [10] A. Menchaca-Méndez, E. Montero, and S. Zapotecas-Martínez, "An improved s-metric selection evolutionary multi-objective algorithm with adaptive resource allocation," *IEEE Access*, vol. 6, pp. 63 382–63 401, 2018.
- [11] S. Jiang, J. Zhang, Y.-S. Ong, A. N. Zhang, and P. S. Tan, "A simple and fast hypervolume indicator-based multiobjective evolutionary algorithm," *IEEE Transactions on Cybernetics*, vol. 45, no. 10, pp. 2202–2213, 2014.
- [12] K. Deb, L. Thiele, M. Laumanns, and E. Zitzler, "Scalable multi-objective optimization test problems," in *Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No. 02TH8600)*, vol. 1. IEEE, 2002, pp. 825–830.
- [13] H. Ishibuchi, R. Imada, S. Yu, and Y. Nojima, "How to specify a reference point in hypervolume calculation for fair performance comparison," *Evolutionary Computation*, vol. 26, no. 3, pp. 1–29, 2018.
- [14] H. Ishibuchi, R. Imada, Y. Setoguchi, and Y. Nojima, "Reference point specification in hypervolume calculation for fair comparison and efficient search," in *Proceedings of the Genetic and Evolutionary Computation Conference*. ACM, 2017, pp. 585–592.
- [15] —, "Hypervolume subset selection for triangular and inverted triangular pareto fronts of three-objective problems," in *Proceedings of the 14th ACM/SIGEVO Conference on Foundations of Genetic Algorithms*. ACM, 2017, pp. 95–110.
- [16] H. Ishibuchi, R. Imada, N. Masuyama, and Y. Nojima, "Dynamic specification of a reference point for hypervolume calculation in sms-emoa," in *2018 IEEE Congress on Evolutionary Computation (CEC)*. IEEE, 2018, pp. 1–8.
- [17] —, "Use of two reference points in hypervolume-based evolutionary multiobjective optimization algorithms," in *International Conference on Parallel Problem Solving from Nature*. Springer, 2018, pp. 384–396.
- [18] H. Ishibuchi, K. Doi, and Y. Nojima, "On the effect of normalization in moea/d for multi-objective and many-objective optimization," *Complex & Intelligent Systems*, vol. 3, no. 4, pp. 279–294, 2017.
- [19] H. Jain and K. Deb, "An evolutionary many-objective optimization algorithm using reference-point based nondominated sorting approach, part ii: handling constraints and extending to an adaptive approach," *IEEE Transactions on Evolutionary Computation*, vol. 18, no. 4, pp. 602–622, 2013.
- [20] T. Ye, C. Ran, X. Zhang, and Y. Jin, "Platemo: A matlab platform for evolutionary multi-objective optimization [educational forum]," *IEEE Computational Intelligence Magazine*, vol. 12, no. 4, pp. 73–87, 2017.
- [21] Q. Zhang and H. Li, "Moea/d: A multiobjective evolutionary algorithm based on decomposition," *IEEE Transactions on evolutionary computation*, vol. 11, no. 6, pp. 712–731, 2007.
- [22] Z. Wang, Y.-S. Ong, J. Sun, A. Gupta, and Q. Zhang, "A generator for multiobjective test problems with difficult-to-approximate pareto front boundaries," *IEEE Transactions on Evolutionary Computation*, 2018.

- [23] H. Trautmann, U. Ligges, J. Mehnen, and M. Preuss, "A convergence criterion for multiobjective evolutionary algorithms based on systematic statistical testing," in *International Conference on Parallel Problem Solving from Nature*. Springer, 2008, pp. 825–836.
- [24] J. L. Guerrero, L. Martí, A. Berlanga, J. García, and J. M. Molina, "Introducing a robust and efficient stopping criterion for moeas," in *IEEE Congress on Evolutionary Computation*. IEEE, 2010, pp. 1–8.
- [25] T. Wagner, H. Trautmann, and B. Naujoks, "Ocd: Online convergence detection for evolutionary multi-objective algorithms based on statistical testing," in *International Conference on Evolutionary Multi-Criterion Optimization*. Springer, 2009, pp. 198–215.
- [26] H. Trautmann, T. Wagner, B. Naujoks, M. Preuss, and J. Mehnen, "Statistical methods for convergence detection of multi-objective evolutionary algorithms," *Evolutionary computation*, vol. 17, no. 4, pp. 493–509, 2009.
- [27] K. Deb and S. Jain, "Running performance metrics for evolutionary multi-objective optimization," 2002.
- [28] O. Rudenko and M. Schoenauer, "A steady performance stopping criterion for pareto-based evolutionary algorithms," in *6th International Multi-Objective Programming and Goal Programming Conference*, 2004.
- [29] T. Wagner, H. Trautmann, and L. Martí, "A taxonomy of online stopping criteria for multi-objective evolutionary algorithms," in *International Conference on Evolutionary Multi-Criterion Optimization*. Springer, 2011, pp. 16–30.
- [30] W. Ericson, "Introductory probability and statistical applications," *Technometrics*, vol. 8, no. 4, pp. 720–722, 1970.
- [31] S. Huband, P. Hingston, L. Barone, and L. While, "A review of multiobjective test problems and a scalable test problem toolkit," *IEEE Transactions on Evolutionary Computation*, vol. 10, no. 5, pp. 477–506, 2006.
- [32] H. Ishibuchi, Y. Setoguchi, H. Masuda, and Y. Nojima, "Performance of decomposition-based many-objective algorithms strongly depends on pareto front shapes," *IEEE Transactions on Evolutionary Computation*, vol. 21, no. 2, pp. 169–190, 2016.