A Component-wise Study of K-RVEA: Observations and Potential Future Developments

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ABSTRACT

Kriging assisted reference vector guided evolutionary algorithm (K-RVEA) is a recently proposed algorithm to deal with many-objective optimization problems involving computationally expensive objective functions. It employs Kriging as the a surrogate and identifies multiple infill locations based on angle penalized distance (APD) metric guided by a set of reference vectors originating from the ideal point. In this paper we investigate the performance implications of the underlying schemes, in particular (a) is APD based selection necessary since it involves an additional parameter, (b) can the full archive be used for surrogate training as opposed to fixed archive size in K-RVEA (c) can the infill solutions be further improved through angle constrained local search and finally (d) understand the limitations of single set of reference vectors and investigate the benefits of dual set of reference vectors (one originating from the ideal and the other from the Nadir). These investigations are based on the suite of standard and inverted DTLZ and WFG problems with up to 10 objectives.

CCS CONCEPTS

• **Applied computing → Multi-criterion optimization and decision-making**;

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1 INTRODUCTION

Multi-objective optimization problems (MOPs) are commonly encountered in practical applications. In the last decade or so, there has been a significant interest in solving MOPs with more than 3 objectives, which have colloquially come to be known as many-objective optimization problems (MaOPs). When the underlying objective functions are computationally expensive, evolutionary algorithms cannot be applied to solve them in their standard form.

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The recently proposed K-RVEA [1] employs Kriging based surrogates to approximate the objective functions and the models are periodically trained using a prescribed number of training samples obtained through true evaluations. The method is built upon a decomposition based framework where search is conducted along a set of systematically sampled reference vectors (RVs) originating from the *ideal point*. Solutions are assigned to its closest RV (closeness in terms smallest acute angle) and the *best* solution along each RV based on angle penalized distance (APD) is carried forward as a member of the parent population for the next generation. The motivation of this study is to understand the performance implications of the key strategies used within K-RVEA, and in particular examine:

1. **Selection metric:** The APD involves a parameter α in the penalty function to control the balance between convergence and diversity across generations. Can similar/better performance be achieved using a simpler parameter-less metric such as Euclidean distance (ED) from the ideal point?
2. **Infill solutions:** In K-RVEA, solutions are generated using recombination and a subset of them eventually are selected as infill solutions which undergo actual evaluation. However, there is an opportunity to conduct an angle constrained local search on the surrogate model to further improve their quality before evaluation.
3. **Surrogate training:** In K-RVEA, surrogates are periodically trained with a finite and fixed size of training samples. Since we are within the realm of limited number of function evaluations, can we derive benefits by using the complete unbounded archive for training and train models in every generation as opposed to periodic training as done in K-RVEA. Such an approach would eliminate two user defined parameters, i.e., the periodicity of training and maximum size of the training set.
4. **Reference vector set:** K-RVEA uses a set of RVs originating from the estimated *ideal point*. Can we improve the performance using a *dual* set of RVs, i.e., one originating from the ideal and the other from the worst point of the current population.

The following variants have been created to test the above.

Table 1: Different K-RVEA Variants.

Variant	Description
K-RVEA	The original K-RVEA
K-RVEA$_{ED}$	Uses ED as the selection metric instead of APD
K-RVEA$_{FA}$	Uses full archive for training instead of fixed size
K-RVEA$_{LS}$	Uses angle constrained surrogate assisted local search
K-RVEA$_{DR}$	Uses dual set of RVs instead of conventional single set

2 NUMERICAL EXPERIMENTS

The performance is assessed using the standard DTLZ [2] and WFG [3] problems and their inverted versions as proposed in [4] with 3, 4, 6, 8 and 10 objectives. The number of variables for all DTLZ problems is set to 10 and for WFG problems, the numbers of variables are set as 10, 10, 9, 9 and 11 for 3, 4, 6, 8 and 10 objective problems. Inverted Generational Distance (IGD) is used as the benchmarking metric. The reference sets for IGD calculation are obtained from the PlatEMO framework [5] for the DTLZ and WFG problems. For the minus variants, the reference sets are derived as suggested in [4]. The spacings in different layers of the RVs, i.e., H_1 and H_2 values for different objectives and the numbers of points in the sets are kept the same as proposed in [1]. Wilcoxon Rank-sum (WRS) test with a 5% confidence level is used to assess the statistical significance of the results. The overall performance is also visually presented using performance profile plots based on the median IGD values (out of 25 independent runs) for all problems in all objectives.

The overall performance of each strategy can be visualized from the performance profile plots presented in Fig. 1. For the standard problems (Fig. 1(a)), the best performing strategy is K-RVEA$_{LS}$ which delivers better median IGD values in ≈63% of the problem instances followed by K-RVEA$_{ED}$ with better median values in ≈58%, K-RVEA$_{FA}$ with better median values in ≈53% and finally, K-RVEA$_{DR}$ with better median values in ≈24% problem instances. For the minus problems (Fig. 1(b)), K-RVEA$_{DR}$ is the best performing strategy with better median values in ≈68% problem instances, while K-RVEA$_{FA}$ has better median values in ≈65%, K-RVEA$_{LS}$ with better median values in ≈62% and K-RVEA$_{ED}$ with better median values in ≈50% problem instances.

Based on WRS test results on both standard and minus problems K-RVEA performs worse than K-RVEA$_{ED}$ (13 wins and 27 losses in normal problems; 26 wins and 29 losses in minus problems). Clearly, use of simple ED as opposed to APD also eliminates the need for user defined parameters α and θ.

One can also observe that for both standard and minus problems , the performance of original K-RVEA is worse than K-RVEA$_{FA}$ (12 wins and 32 losses in normal problems; 21 wins and 39 losses in minus problems). Although using the full archive information would mean increase in model training time, it can offer significant benefits in terms of quality of final solutions.

Once again for both normal and minus problems, one can observe poor performance of original K-RVEA when compared with K-RVEA$_{LS}$ (20 wins and 30 losses for normal problems and 22 wins and 40 losses for minus problems). Clearly, improving the infill solutions though surrogate assisted angle constrained local search is beneficial although it incurs additional cost of local search.

Performance with dual set of RVs is particularly interesting. For normal problems, according to the WRS test, the original K-RVEA outperforms K-RVEA$_{DR}$ (55 wins and 16 losses). On the other hand for minus problems, performance of original K-RVEA is relatively poor (21 wins and 44 losses).

3 CONCLUSIONS AND FUTURE DIRECTIONS

The observations clearly reveal a number of areas which need careful consideration. The first relates to the selection metric APD. One can use several scalarizing functions and although they generate different preference structures, such a choice is less likely to influence the performance since members of a subpopulation are only compared among each other. A parameter free metric such as Euclidean distance may be equally effective. Secondly, using a local search to improve infill solutions, as well as building surrogate models with all available information (in the archive) is certainly beneficial. Finally, while use of a dual set of reference vectors with the choice guided by the energy metric in K-RVEA$_{DR}$ is far from perfect, generic adaptation is inherently going to be challenging.

Table 2: Test results with the IGD metric based on 25 runs across standard DTLZ and WFG problems over different numbers of objectives.

Problem Types	M	K-RVEA$_{ED}$ (n/w/l/t)	K-RVEA$_{FA}$ (n/w/l/t)	K-RVEA$_{LS}$ (n/w/l/t)	K-RVEA$_{DR}$ (n/w/l/t)
Standard Problems	3	16/6/4/6	16/3/7/6	16/0/14/2	16/11/1/4
	4	16/3/5/8	16/3/5/8	16/4/4/8	16/8/6/2
	6	16/1/3/6	16/1/6/9	16/8/3/5	16/11/4/1
	8	16/2/8/6	16/4/8/4	16/5/5/6	16/12/2/2
	10	16/1/7/8	16/1/6/9	16/3/4/9	16/13/3/0
	Total =	80/13/27/40	80/12/32/36	80/20/30/30	80/55/16/9
Minus Problems	3	13/5/8/0	13/5/8/0	13/5/8/0	13/5/8/0
	4	13/5/8/0	13/5/8/0	13/5/8/0	13/5/8/0
	6	13/4/6/3	13/3/9/1	13/4/9/0	13/3/10/0
	8	13/7/3/3	13/4/5/4	13/4/6/3	13/4/9/0
	10	13/5/4/4	13/4/9/4	13/4/9/0	13/4/9/0
	Total =	65/26/29/10	65/21/39/5	65/22/40/3	65/21/44/0

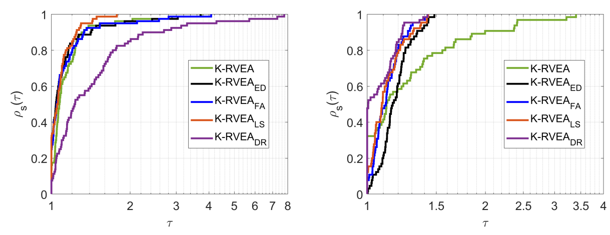

Figure 1: Performance profile plots considering the median IGD values of 25 independent runs (a) standard problems (b) minus problems.

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