

ADAPTIVE SURROGATE-BASED MULTI-CRITERIA OPTIMIZATION

*Alexis I. Pospelov^{1,2,†}, Fedor V. Gubarev^{1,2,‡} and Alexey M. Nazarenko^{1,2,§}

¹ DATADVANCE, Pokrovsky blvd. 3/1B, 109028, Moscow, Russia, datadvance.net,

² IITP RAS, Bolshoy Karetny per. 19, 127994, Moscow, Russia, www.iitp.ru

[†] alexis.pospelov@datadvance.net,

[‡] fedor.gubarev@datadvance.net, gubarev@iitp.ru

[§] alexey.nazarenko@datadvance.net

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In many engineering applications phenomena to be studied are so complicated, that we have to submit to strict limitations on amount of physical and/or computer experiments. In this case one says that model under consideration is expensive to evaluate. Most practically relevant models of this sort do not provide any additional (i.e. analytical) information apart from plain model responses. Usually, these “black boxes” describe quite complex landscapes with many local minima.

It’s common that the goal of study is to find efficient solutions taking into account different contradictory requirements, which leads to formulating investigated problems in a form of multi-criteria optimization problem. Computational limitations become especially pressing in multi-criteria optimization, which usually requires much more efforts to discover Pareto frontier.

To deal with above problems special methods have to developed, which at the same time should use restricted amount of evaluations of the investigated model and be global to fight with multi-modality of the problem and be able to effectively approximate Pareto frontier. In this work we present approach that pretends to overcome described obstacles.

The three main components of proposed approach are following.

First is an adaptive Chebyshev scalarization. Scalarization allows reducing multi-criteria problem to a series of single-criterion optimization subproblems. Chebyshev scalarization is used in multi-criteria optimization, when non-convex Pareto frontier is to be discovered. However the scalarization should be employed very accurately because carefree application of scalarization may lead to non-uniform frontier discovery and necessity in repeated

solution of optimization subproblems, both of each may dramatically increase the number of evaluations required to find an adequate approximation of Pareto frontier. Uniformity of frontier discovery can be significantly improved (and as a consequence the number of scalarization subproblems to be solved can be greatly reduced) by adaptive selection of scalarization parameters [1]. In the approach incrementally growing knowledge about Pareto frontier during optimization is used to select scalarization parameters to direct search into the most promising areas.

The second component is to use surrogate models to optimize scalarization of criteria using small amount of evaluations and at the same time to tie together usually different scalarization subtasks. All expensive evaluations made during solution of prior subtasks are used to build more and more precise models thus making subsequent subtasks incrementally easier.

The third ingredient is generalization of probability of improvement method. The corner stone of surrogate based optimization is the right balance between exploration and exploitation of an optimized function, which need to be kept to make the optimization global and accurate at the same time. To keep this balance instead of surrogates of original models the special derivative criteria is optimized. In this work we generalize probability of improvement criterion [2] to be utilized in scalarization subproblems.

The approach described above was implemented in pSeven powered by MACROS technology and successfully applied to number of artificial and real-life tasks.

REFERENCES

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